

3.10. Methodology for Estimating CH₄ Emissions from Enteric Fermentation

The steps outlined in this annex were used to estimate methane emissions from enteric fermentation for the years 1990 through 2022. Methane emissions from enteric fermentation were estimated for seven livestock categories: cattle, horses, sheep, swine, goats, American bison, and the non-horse equines (mules and asses). Emissions from cattle represent the majority of U.S. emissions from enteric fermentation; consequently, a more detailed IPCC Tier 2 methodology was used to estimate emissions from cattle. The IPCC Tier 1 methodology was used to estimate emissions for the other types of livestock, including horses, goats, sheep, swine, American bison, and mules and asses (IPCC 2006).

Estimate Methane Emissions from Cattle

This section describes the process used to estimate CH₄ emissions from enteric fermentation from cattle using the Cattle Enteric Fermentation Model (CEFM). The CEFM was developed based on guidance provided in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC 2006) and uses information on population, energy requirements, digestible energy, and CH₄ conversion rates to estimate CH₄ emissions.⁷⁵ The emission methodology consists of the following three steps: (1) characterize the cattle population to account for animal population categories with different emission profiles; (2) characterize cattle diets to generate information needed to estimate emission factors; and (3) estimate emissions using these data and the IPCC Tier 2 equations.

Step 1: Characterize U.S. Cattle Population

The CEFM's state-level cattle population estimates are based on data obtained from the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service Quick Stats database (USDA 2023). State-level cattle population estimates are shown by animal type for 2022 in Table A-124. A national-level summary of the annual average populations upon which all livestock-related emissions (both Enteric Fermentation and Manure Management) are based is provided in Table A-125, to ensure consistency. Cattle populations used in the Enteric Fermentation source category for the 1990 to 2022 Inventory were estimated using the cattle transition matrix in the CEFM, which uses January 1 USDA population estimates and weight data to simulate the population of U.S. cattle from birth to slaughter, and results in an estimate of the number of animals in a particular cattle grouping while taking into account the monthly rate of weight gain, the average weight of the animals, and the death and calving rates. The use of supplemental USDA data and the cattle transition matrix in the CEFM results in cattle population estimates for this sector differing slightly from the January 1 or July 1 USDA point estimates and the cattle population data obtained from the Food and Agriculture Organization of the United Nations (FAO). See the Enteric Fermentation chapter for more details about this approach.

Table A-124: 2022 Cattle Population Estimates, by Animal Type and State (1,000 head)

State	Dairy		Dairy		Bulls	Beef		Beef		Steer Stockers	Heifer	
	Calves	Cows	7-11 Months	12-23 Months		Calves	Cows	7-11 Months	12-23 Months		Stockers	Stockers
Alabama	2	3	1	1	43	342	672	24	60	22	23	8
Alaska	0	0	0	0	5	4	8	0	1	0	0	0
Arizona	100	194	35	84	20	87	171	6	14	133	11	287
Arkansas	3	5	1	2	55	460	905	31	76	53	33	15
California	891	1,720	221	531	60	346	680	26	64	294	103	585
Colorado	105	202	33	80	45	324	638	31	76	368	271	1,217
Conn.	10	19	3	7	1	2	5	0	1	0	1	0
Delaware	1	3	0	1	0	1	2	0	0	1	0	0
Florida	54	105	9	21	55	455	895	28	70	11	11	4
Georgia	43	83	7	17	30	248	487	23	56	18	11	5
Hawaii	0	1	0	1	4	40	79	2	6	4	2	1
Idaho	338	652	102	245	40	253	498	22	53	147	103	332

⁷⁵ Additional information on the Cattle Enteric Fermentation Model can be found in ICF (2006).

Illinois	42	81	12	29	18	172	339	12	31	90	41	226
Indiana	96	186	17	42	16	94	184	8	20	44	21	113
Iowa	117	225	35	84	60	460	905	36	90	593	271	1,233
Kansas	88	169	46	112	85	722	1,421	61	151	938	784	2,762
Kentucky	23	44	10	24	60	491	966	28	70	101	50	19
Louisiana	5	9	1	2	30	229	451	18	45	11	9	3
Maine	13	26	4	9	2	5	10	1	2	2	1	1
Maryland	21	41	8	18	4	21	42	2	5	6	3	8
Mass.	5	10	2	4	1	4	8	1	2	1	0	0
Michigan	225	434	44	106	15	49	96	5	13	80	21	173
Minn.	238	460	61	147	30	183	360	19	48	225	67	405
Miss.	4	7	1	3	39	243	478	21	51	24	17	7
Missouri	36	69	9	21	110	987	1,941	68	168	193	105	89
Montana	6	11	1	3	95	660	1,299	73	179	97	85	48
Nebraska	30	58	9	21	110	916	1,802	79	196	1,173	725	2,942
Nevada	16	31	3	6	13	124	244	9	21	16	13	3
N.Hamp.	5	11	2	4	1	2	4	0	1	1	0	0
N.Jersey	2	4	1	2	1	4	8	0	1	1	1	0
N.Mexico	151	292	36	87	25	230	453	16	39	46	32	13
New York	321	620	96	231	20	51	100	9	22	21	18	23
N.Car.	20	39	4	10	31	184	361	14	35	19	12	5
N.Dakota	8	15	2	6	60	475	935	41	102	143	105	43
Ohio	128	248	35	84	30	159	312	15	36	101	28	158
Oklahoma	20	39	6	14	170	1,078	2,121	91	224	464	248	337
Oregon	65	125	16	38	40	257	505	23	56	78	55	131
Penn	243	470	57	136	20	97	190	12	29	64	22	74
R.Island	0	1	0	0	0	1	1	0	0	0	0	0
S.Car.	5	9	1	3	12	80	158	7	16	5	4	2
S.Dakota	88	170	12	28	105	813	1,600	84	207	345	227	472
Tenn.	14	27	6	14	60	454	893	27	67	62	39	17
Texas	324	625	70	168	330	2,250	4,425	161	398	1,209	775	3,077
Utah	49	95	16	38	23	168	330	16	39	41	28	23
Vermont	62	120	15	36	3	8	15	1	3	2	3	1
Virginia	37	71	10	24	38	305	599	20	50	69	32	18
Wash.	135	261	38	91	18	114	224	12	31	87	60	237
W.Virg.	3	5	1	1	14	96	188	7	17	18	10	4
Wisconsin	660	1,275	192	461	30	150	295	19	48	184	39	280
Wyoming	5	9	1	3	35	346	681	33	81	74	62	73

Table A-125: Cattle Population Estimates from the CEFM Transition Matrix for 1990–2022 (1,000 head)

Livestock Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Dairy										
Dairy Calves (0–6 months)	5,369	5,091	4,951	4,628	4,666	4,833	4,834	4,813	4,876	4,855
Dairy Cows	10,015	9,482	9,183	9,004	9,087	9,432	9,353	9,343	9,442	9,377
Dairy Replacements 7–11 months	1,214	1,216	1,196	1,257	1,351	1,400	1,391	1,365	1,326	1,289
Dairy Replacements 12–23 months	2,915	2,892	2,812	2,905	3,194	3,341	3,304	3,272	3,216	3,105
Beef										

Beef Calves (0–6 months)	16,909	18,177	17,431	16,918	16,067	16,221	15,892	15,830	15,602	15,244
Bulls	2,160	2,385	2,293	2,214	2,190	2,252	2,253	2,237	2,211	2,110
Beef Cows	32,455	35,190	33,575	32,674	31,440	31,466	31,691	31,339	30,844	29,983
Beef Replacements 7–11 months	1,269	1,493	1,313	1,363	1,238	1,420	1,380	1,367	1,321	1,242
Beef Replacements 12–23 months	2,967	3,637	3,097	3,171	3,050	3,444	3,321	3,253	3,255	3,070
Steer Stockers	10,321	11,716	8,724	8,185	8,234	7,633	7,745	7,614	7,686	7,682
Heifer Stockers	5,946	6,699	5,371	5,015	5,061	4,595	4,500	4,472	4,629	4,584
Feedlot Cattle	9,549	11,064	13,006	12,652	13,204	14,690	14,917	14,949	15,554	15,474

The population transition matrix in the CEFM simulates the U.S. cattle population over time and provides an estimate of the population age and weight structure by cattle type on a monthly basis.⁷⁶ Since cattle often do not remain in a single population type for an entire year (e.g., calves become stockers, stockers become feedlot animals), and emission profiles vary both between and within each cattle type, these monthly age groups are tracked in the CEFM to obtain more accurate emission estimates than would be available from annual point estimates of population (such as available from USDA statistics) and weight for each cattle type.

The transition matrix tracks both dairy and beef populations, and divides the populations into males and females, and subdivides the population further into specific cattle groupings for calves, replacements, stockers, feedlot, and mature animals. The matrix is based primarily on two types of data: population statistics and weight statistics (including target weights, slaughter weights, and weight gain). Using the weight data, the transition matrix simulates the growth of animals over time by month. The matrix also relies on supplementary data, such as feedlot placement statistics, slaughter statistics, death rates, and calving rates, described in further detail below.

The basic method for tracking population of animals per category is based on the number of births (or graduates) into the monthly age group minus those animals that die or are slaughtered and those that graduate to the next category (such as stockers to feedlot placements).

Each stage in the cattle lifecycle was modeled to simulate the cattle population from birth to slaughter. This level of detail accounts for the variability in CH₄ emissions associated with each life stage. Given that a stage can last less than one year (e.g., calves are usually weaned between 4 and 6 months of age), each is modeled on a per-month basis. The type of cattle also influences CH₄ emissions (e.g., beef versus dairy). Consequently, there is an independent transition matrix for each of three separate lifecycle phases, 1) calves, 2) replacements and stockers, and 3) feedlot animals. In addition, the number of mature cows and bulls are tabulated for both dairy and beef stock. The transition matrix estimates total monthly populations for all cattle subtypes. These populations are then reallocated to the state level based on the percent of the cattle type reported in each state in the January 1 USDA data. Each lifecycle is discussed separately below, and the categories tracked are listed in Table A-126.

Table A-126: Cattle Population Categories Used for Estimating CH₄ Emissions

Dairy Cattle	Beef Cattle
Calves	Calves
Heifer Replacements	Heifer Replacements
Cows	Heifer and Steer Stockers
	Animals in Feedlots (Heifers & Steer)
	Cows
	Bulls ^a

^a Bulls (beef and dairy) are accounted for in a single category.

The key variables tracked for each of these cattle population categories are as follows:

⁷⁶ Mature animal populations are not assumed to have significant monthly fluctuations, and therefore the populations utilized are the January estimates downloaded from USDA (2023).

Calves. Although enteric emissions are only calculated for 4- to 6-month old calves, it is necessary to calculate populations from birth as emissions from manure management require total calf populations and the estimates of populations for older cattle rely on the available supply of calves from birth. The number of animals born on a monthly basis was used to initiate monthly cohorts and to determine population age structure. The number of calves born each month was obtained by multiplying annual births by the percentage of births per month. Annual birth information for each year was taken from USDA (2021). For dairy cows, monthly birth data are not readily available, so the number of births is assumed to be distributed equally throughout the year (approximately 8.3 percent per month) while beef births are distributed according to Table A-127, based on approximations from the National Animal Health Monitoring System (NAHMS) (USDA/APHIS/VIS 1998, 1994, 1993). To determine whether calves were born to dairy or beef cows, the dairy cow calving rate (USDA/APHIS/VIS 2002; USDA/APHIS/VIS 1996) was multiplied by the total dairy cow population to determine the number of births attributable to dairy cows, with the remainder assumed to be attributable to beef cows. Total annual calf births are obtained from USDA and distributed into monthly cohorts by cattle type (beef or dairy). Calf growth is modeled by month, based on estimated monthly weight gain for each cohort (approximately 61 pounds per month). The total calf population is modified through time to account for veal calf slaughter at 4 months and a calf death loss of 0.35 percent annually (distributed across age cohorts up to 6 months of age). An example of a transition matrix for calves is shown in Table A-128. Note that 1- to 6-month-old calves in January of each year have been tracked through the model based on births and death loss from the previous year.

Table A-127: Estimated Beef Cow Births by Month

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
7%	15%	28%	22%	9%	3%	2%	2%	3%	4%	3%	3%

Table A-128: Example of Monthly Average Populations from Calf Transition Matrix (1,000 head)

Age (month)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
6	1,187	1,179	1,414	1,648	1,585	1,572	2,437	4,522	7,834	6,352	2,982	1,513
5	1,180	1,415	1,649	1,585	1,573	2,438	4,523	7,837	6,355	2,983	1,515	1,139
4	1,448	1,680	1,618	1,601	2,465	4,554	7,869	6,391	3,016	1,545	1,171	1,162
3	1,681	1,619	1,602	2,466	4,555	7,872	6,394	3,017	1,546	1,172	1,163	1,423
2	1,621	1,603	2,467	4,557	7,875	6,396	3,018	1,547	1,172	1,163	1,424	1,650
1	1,604	2,469	4,559	7,878	6,398	3,019	1,547	1,173	1,164	1,425	1,651	1,590
0	2,471	4,562	7,882	6,401	3,020	1,548	1,173	1,164	1,426	1,652	1,591	1,574

Note: As outlined in grey as an example, the cohort starting at age 0 months on January 1 is tracked in order to illustrate how a single cohort moves through the transition matrix. Each month, the cohort reflects the decreases in population due to the estimated 0.35 percent annual death loss, and between months 4 and 5, a more significant loss is seen than in other months due to estimated veal slaughter.

Replacements and Stockers. At 7 months of age, calves “graduate” and are separated into the applicable cattle types: replacements (cattle raised to give birth), or stockers (cattle held for conditioning and growing on grass or other forage diets). First the number of replacements required for beef and dairy cattle are calculated based on estimated death losses and population changes between beginning and end of year population estimates. Based on the USDA estimates for “replacement beef heifers” and “replacement dairy heifers,” the transition matrix for the replacements is back-calculated from the known animal totals from USDA, and the number of calves needed to fill that requirement for each month is subtracted from the known supply of female calves. All female calves remaining after those needed for beef and dairy replacements are removed become “stockers” that can be placed in feedlots (along with all male calves). During the stocker phase, animals are subtracted out of the transition matrix for placement into feedlots based on feedlot placement statistics from USDA (2023).

The data and calculations that occur for the stocker category include matrices that estimate the population of backgrounding heifers and steer, as well as a matrix for total combined stockers. The matrices start with the beginning of year populations in January and model the progression of each cohort. The age structure of the January population is based on estimated births by month from the previous two years, although in order to balance the population properly, an adjustment is added that slightly reduces population percentages in the older populations. The populations are

modified through addition of graduating calves (added in month 7, bottom row of Table A-129) and subtraction through death loss and animals placed in feedlots. Eventually, an entire cohort population of stockers may reach zero, indicating that the complete cohort has been transitioned into feedlots. An example of the transition matrix for stockers is shown in Table A-129.

Table A-129: Example of Monthly Average Populations from Stocker Transition Matrix (1,000 head)

Age (month)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
23	190	183	91	28	11	6	5	5	3	1	0	0
22	328	148	43	15	8	6	6	5	3	1	0	186
21	266	70	22	11	8	8	7	5	3	33	186	322
20	126	36	17	11	10	9	7	5	77	270	322	261
19	64	27	17	13	12	9	6	123	382	512	262	123
18	49	27	20	16	11	9	157	497	764	440	123	63
17	48	33	24	15	11	209	582	1,024	676	211	64	48
16	59	38	23	15	269	714	1,217	920	326	297	48	48
15	69	37	22	359	865	1,515	1,101	446	605	62	48	58
14	66	36	547	1,095	1,857	1,380	535	924	80	48	58	67
13	66	888	1,538	2,364	1,697	672	1,214	102	48	58	67	65
12	1,019	1,690	2,658	1,906	796	1,622	272	89	58	68	65	64
11	1,892	2,920	2,143	894	1,976	351	216	161	138	128	119	1,030
10	3,271	2,369	1,002	2,326	456	290	328	436	405	380	1,258	2,429
9	2,656	1,122	2,633	558	431	515	625	589	576	1,445	3,006	5,337
8	1,252	3,062	736	575	726	949	841	853	1,634	3,421	6,313	5,055
7	3,433	869	863	1,069	1,277	1,221	1,212	1,983	3,835	6,777	5,461	2,468

Note: As outlined in grey as an example, the cohort starting at age 7 months on January 1 is tracked in order to illustrate how a single cohort moves through the transition matrix. Each month, the cohort reflects the decreases in population due to the estimated 0.35 percent annual death loss and loss due to placement in feedlots (the latter resulting in the majority of the loss from the matrix).

To ensure a balanced population of both stockers and placements, additional data tables are used in the stocker matrix calculations. The tables summarize the placement data by weight class and month and are based on the total number of animals within the population that are available to be placed in feedlots and the actual feedlot placement statistics provided by USDA (2023). In cases where there are discrepancies between the USDA estimated placements by weight class and the calculated animals available by weight, the model pulls available stockers from the next highest weight category if available. If there are still not enough animals to fulfill requirements, the model pulls animals from the next lowest weight category. In the current time series, this method was able to ensure that total placement data matched USDA estimates, and no shortfalls have occurred.

In addition, average weights were tracked for each monthly age group using starting weight and monthly weight gain estimates. Weight gain (i.e., pounds per month) was estimated based on weight gain needed to reach a set target weight, divided by the number of months remaining before target weight was achieved. Birth weight was assumed to be 88 pounds for both beef and dairy animals. Weaning weights were estimated at 515 pounds. Other reported target weights were available for 12-, 15-, 24-, and 36-month-old animals, depending on the animal type. Beef cow mature weight was taken from measurements provided for a major British Bos taurus breed (Enns 2008) and increased during the time series through 2007.⁷⁷ Bull mature weight was calculated as 1.5 times the beef cow mature weight (Doren et al. 1989). Beef replacement weight was calculated as 70 percent of mature weight at 15 months and 85 percent of mature weight at 24 months. As dairy weights are not a trait that is typically tracked, mature weight for dairy cows was estimated at 1,500 pounds for all years, based on expert judgement by Kris Johnson (2010) and an estimate from

⁷⁷ Mature beef weight is held constant after 2007 but future *Inventory* submissions will incorporate known trends through 2007 and extrapolate to future years, as noted in the Planned Improvements section of 5.1 Enteric Fermentation.

Holstein Association USA (2010).⁷⁸ Dairy replacement weight at 15 months was assumed to be 875 pounds and 1,300 pounds at 24 months. Live slaughter weights were estimated from dressed slaughter weight (USDA 2021a) divided by 0.63. This ratio represents the dressed weight (i.e., weight of the carcass after removal of the internal organs), to the live weight (i.e., weight taken immediately before slaughter). The annual typical animal mass for each livestock type is presented in Table A-130.

Weight gain for stocker animals was based on monthly gain estimates from Johnson (1999) for 1989, and from average daily estimates from Lippke et al. (2000), Pinchack et al. (2004), Platter et al. (2003), and Skogerboe et al. (2000) for 2000. Interim years were calculated linearly, as shown in Table A-131, and weight gain was held constant starting in 2000. Table A-131 provides weight gains that vary by year in the CEFM.

Table A-130: Typical Animal Mass (lbs)

Year/Cattle Type	Calves	Dairy Cows ^a	Dairy Replacements ^b	Bulls ^a	Beef Cows ^a	Beef Replacements ^b	Steer Stockers ^b	Heifer Stockers ^b	Steer Feedlot ^b	Heifer Feedlot ^b
1990	269	1,499	899	1,830	1,220	819	691	651	923	845
1991	270	1,499	897	1,836	1,224	821	694	656	933	855
1992	269	1,499	897	1,893	1,262	840	714	673	936	864
1993	270	1,499	898	1,918	1,279	852	721	683	929	863
1994	270	1,499	897	1,918	1,279	853	720	688	943	875
1995	270	1,499	897	1,921	1,281	857	735	700	947	879
1996	269	1,499	898	1,926	1,284	858	739	707	939	878
1997	270	1,499	899	1,927	1,285	860	736	707	938	876
1998	270	1,499	896	1,942	1,295	865	736	709	956	892
1999	270	1,499	899	1,936	1,291	861	730	708	959	894
2000	270	1,499	896	1,906	1,271	849	719	702	960	898
2001	270	1,499	897	1,906	1,271	850	725	707	963	900
2002	270	1,499	896	1,912	1,275	851	725	707	981	915
2003	270	1,499	899	1,960	1,307	871	718	701	972	904
2004	270	1,499	896	1,983	1,322	877	719	702	966	904
2005	270	1,499	894	1,989	1,326	879	717	706	974	917
2006	270	1,499	897	2,010	1,340	889	724	712	983	925
2007	270	1,499	896	2,020	1,347	894	720	706	991	928
2008	270	1,499	897	2,020	1,347	894	720	704	999	938
2009	270	1,499	895	2,020	1,347	894	730	715	1007	947
2010	270	1,499	897	2,020	1,347	896	726	713	996	937
2011	270	1,499	897	2,020	1,347	891	721	712	989	932
2012	270	1,499	899	2,020	1,347	892	714	706	1003	945
2013	270	1,499	898	2,020	1,347	892	718	709	1016	958
2014	270	1,499	895	2,020	1,347	888	720	713	1021	960
2015	270	1,499	896	2,020	1,347	890	717	714	1037	982
2016	270	1,499	898	2,020	1,347	892	721	718	1047	991
2017	270	1,499	896	2,020	1,347	894	714	709	1037	977
2018	270	1,499	898	2,020	1,347	894	708	701	1030	972
2019	270	1,499	897	2,020	1,347	893	710	698	1032	972
2020	271	1,499	899	2,020	1,347	893	710	698	1045	983
2021	273	1,499	900	2,020	1,347	896	711	700	1056	989
2022	271	1,499	899	2,020	1,347	896	716	701	1059	989

^a Input into the model.

^b Annual average calculated in model based on age distribution.

⁷⁸ Mature dairy weight is based solely on Holstein weight, so could be higher than the national average. Future *Inventory* submissions will consider other dairy breeds, as noted in the Planned Improvements section of 5.1 Enteric Fermentation.

Table A-131: Weight Gains that Vary by Year (lbs)

Year/Cattle Type	Steer Stockers to 12 months(lbs/day)	Steer Stockers to 24 months (lbs/day)	Heifer Stockers to 12 months(lbs/day)	Heifer Stockers to 24 months(lbs/day)
1990	1.53	1.23	1.23	1.08
1991	1.56	1.29	1.29	1.15
1992	1.59	1.35	1.35	1.23
1993	1.62	1.41	1.41	1.30
1994	1.65	1.47	1.47	1.38
1995	1.68	1.53	1.53	1.45
1996	1.71	1.59	1.59	1.53
1997	1.74	1.65	1.65	1.60
1998	1.77	1.71	1.71	1.68
1999	1.80	1.77	1.77	1.75
2000–onwards	1.83	1.83	1.83	1.83

Sources: Enns (2008), Johnson (1999), Lippke et al. (2000), NRC (1999), Pinchack et al. (2004), Platter et al. (2003), Skogerboe et al. (2000).

Feedlot Animals. Feedlot placement statistics from USDA provide data on the placement of animals from the stocker population into feedlots on a monthly basis by weight class. The model uses these data to shift a sufficient number of animals from the stocker cohorts into the feedlot populations to match the reported placement data. After animals are placed in feedlots, they progress through two steps. First, animals spend 25 days on a step-up diet to become acclimated to the new feed type (e.g., more grain than forage, along with new dietary supplements); during this time weight gain is estimated to be 2.7 to 3 pounds per day (Johnson 1999). Animals are then switched to a finishing diet (concentrated, high energy) for a period of time before they are slaughtered. Weight gain during finishing diets is estimated to be 2.9 to 3.3 pounds per day (Johnson 1999). The length of time an animal spends in a feedlot depends on the start weight (i.e., placement weight), the rate of weight gain during the start-up and finishing phase of diet, and the target weight (as determined by weights at slaughter). Additionally, animals remaining in feedlots at the end of the year are tracked for inclusion in the following year’s emission and population counts. For 1990 to 1995, only the total placement data were available, therefore placements for each weight category (categories displayed in Table A-132) for those years are based on the average of monthly placements from the 1996 to 1998 reported figures. Placement data is available by weight class for all years from 1996 onward. Table A-132 provides a summary of the reported feedlot placement statistics for 2022.

Table A-132: Feedlot Placements in the United States for 2022 (Number of animals placed/1,000 Head)

Weight Placed When:	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
< 600 lbs	420	365	380	365	365	365	400	430	445	535	535	450
600 – 700 lbs	445	330	330	270	270	270	280	320	330	460	460	425
700 – 800 lbs	550	505	535	415	465	370	405	465	440	445	400	415
> 800 lbs	589	668	760	774	769	629	679	895	865	645	510	494
Total	2,004	1,868	2,005	1,824	1,869	1,634	1,764	2,110	2,080	2,085	1,905	1,784

Note: Totals may not sum due to independent rounding.

Source: USDA (2023).

Mature Animals. Energy requirements and, hence, composition of diets, level of intake, and emissions for mature animals are greatly influenced by whether the animal is pregnant or lactating. Information is therefore needed on the percentage of all mature animals that are pregnant each month, as well as milk production, to estimate CH₄ emissions. A weighted average percent of pregnant cows each month was estimated using information on births by month and average pregnancy term. For beef cattle, a weighted average total milk production per animal per month was estimated using information on typical lactation cycles and amounts (NRC 1999), and data on births by month. This process results in a range of weighted monthly lactation estimates expressed as pounds per animal per month. The monthly estimates for daily milk production by beef cows are shown in Table A-133. Annual estimates for dairy cows were taken from USDA milk production statistics. Dairy lactation estimates for 1990 through 2022 are shown in Table A-134. Beef and dairy cow

and bull populations are assumed to remain relatively static throughout the year, as large fluctuations in population size are assumed to not occur. These estimates are taken from the USDA beginning and end of year population datasets.

Table A-133: Estimates of Average Monthly Milk Production by Beef Cows (lbs/cow)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Beef Cow Milk Production (lbs/head)	3.3	5.1	8.7	12.0	13.6	13.3	11.7	9.3	6.9	4.4	3.0	2.8

Table A-134: Dairy Lactation Rates by State (lbs/ year/cow)

State/Year	1990	2000	2005	2010	2018	2019	2020	2021	2022
Alabama	12,214	13,920	14,000	14,182	14,600	12,000	14,667	13,000	10,667
Alaska	13,300	14,500	12,273	11,833	9,333	4,455	5,333	6,111	5,556
Arizona	17,500	21,820	22,679	23,452	23,909	24,096	24,445	24,333	24,223
Arkansas	11,841	12,436	13,545	12,750	12,333	13,400	12,800	12,000	11,250
California	18,456	21,130	21,404	23,025	23,301	23,533	23,990	24,338	24,267
Colorado	17,182	21,618	22,577	23,664	25,892	25,844	26,142	25,985	25,922
Connecticut	15,606	17,778	19,200	19,158	22,474	22,526	23,053	22,895	23,889
Delaware	13,667	14,747	16,622	16,981	19,063	17,976	18,553	17,333	17,815
Florida	14,033	15,688	16,591	18,711	19,833	20,224	20,230	20,093	19,928
Georgia	12,973	16,284	17,259	17,658	21,277	21,598	21,877	21,927	22,043
Hawaii	13,604	14,358	12,889	13,316	16,950	4,455	5,333	6,111	5,556
Idaho	16,475	20,816	22,332	22,647	24,870	25,011	25,174	25,172	25,348
Illinois	14,707	17,450	18,827	18,400	20,867	20,810	21,530	21,585	21,425
Indiana	14,590	16,568	20,295	20,094	22,754	22,899	23,683	23,641	23,726
Iowa	15,118	18,298	20,641	20,676	23,955	24,271	24,651	24,504	24,658
Kansas	12,576	16,923	20,505	20,983	23,321	23,429	23,682	23,831	23,948
Kentucky	10,947	12,841	12,896	14,769	18,345	18,840	19,563	19,739	20,578
Louisiana	11,605	12,034	12,400	11,750	13,818	13,500	13,400	14,000	12,444
Maine	14,619	17,128	18,030	18,344	20,600	21,414	21,963	21,185	21,308
Maryland	13,461	16,083	16,099	18,537	20,556	19,535	20,976	20,857	20,537
Massachusetts	14,871	17,091	17,059	17,286	18,364	19,300	20,000	19,500	20,889
Michigan	15,394	19,017	21,635	23,277	26,409	26,725	27,174	27,102	27,430
Minnesota	14,127	17,777	18,091	19,366	21,784	22,147	22,694	22,859	23,128
Mississippi	12,081	15,028	15,280	13,118	14,333	15,750	16,375	15,143	12,857
Missouri	13,632	14,662	16,026	14,596	14,386	14,103	14,276	14,225	14,045
Montana	13,542	17,789	19,579	20,643	22,833	21,583	21,167	22,091	22,300
Nebraska	13,866	16,513	17,950	19,797	24,000	24,293	24,746	24,534	24,842
Nevada	16,400	19,000	21,680	23,714	22,938	23,091	23,879	25,121	24,813
New Hampshire	15,100	17,333	18,875	19,600	20,750	21,727	21,455	20,636	21,900
New Jersey	13,538	15,250	16,000	17,500	18,333	20,000	20,200	22,500	21,750
New Mexico	18,815	20,944	21,192	24,551	25,106	25,113	24,755	24,541	24,819
New York	14,658	17,378	18,639	20,807	23,888	24,118	24,435	24,785	25,096
North Carolina	15,220	16,746	18,741	19,682	21,295	21,476	21,829	22,925	23,385
North Dakota	12,624	14,292	14,182	18,286	22,267	21,733	21,867	22,333	22,786
Ohio	13,767	17,027	17,567	19,446	21,359	21,614	22,118	21,946	22,076
Oklahoma	12,327	14,440	16,480	17,125	18,125	17,829	17,452	18,077	18,333
Oregon	16,273	18,222	18,876	20,331	20,577	20,913	20,929	20,976	20,921
Pennsylvania	14,726	18,081	18,722	19,847	20,534	20,629	21,326	21,338	21,259
Rhode Island	14,250	15,667	17,000	17,727	16,429	17,667	21,800	20,200	20,000
South Carolina	12,771	16,087	16,000	17,875	17,286	17,167	18,600	17,889	17,889
South Dakota	12,257	15,516	17,741	20,478	22,364	22,480	23,111	23,090	23,117
Tennessee	11,825	14,789	15,743	16,346	17,135	17,219	18,067	18,143	18,296
Texas	14,350	16,503	19,646	21,375	23,948	24,513	24,966	25,079	25,579

Utah	15,838	17,573	18,875	21,898	23,220	23,061	23,229	23,167	23,323
Vermont	14,528	17,199	18,469	18,537	21,126	21,405	21,336	21,392	21,644
Virginia	14,213	15,833	16,990	18,095	19,699	19,867	20,293	20,151	20,343
Washington	18,532	22,644	23,270	23,514	24,318	24,225	24,346	24,000	24,089
West Virginia	11,250	15,588	14,923	15,700	15,857	15,000	14,833	15,000	15,000
Wisconsin	13,973	17,306	18,500	20,630	24,002	24,123	24,423	24,889	25,064
Wyoming	12,337	13,571	14,878	20,067	23,700	24,433	25,173	25,918	25,763

Source: USDA (2023).

Step 2: Characterize U.S. Cattle Population Diets

To support development of digestible energy (DE, the percent of gross energy intake digested by the animal) and CH₄ conversion rate values (Y_m, the fraction of gross energy converted to CH₄) for each of the cattle population categories, data were collected on diets considered representative of different regions. For both grazing animals (stockers, beef cows, and beef replacement heifers) and animals being fed mixed rations (i.e., feedlot steers and heifers), representative regional diets were estimated using information collected from state livestock specialists, the USDA, expert opinion, and other literature sources. The designated regions for this analysis for dairy cattle for all years and foraging beef cattle from 1990 through 2006 are shown in Table A-135. For foraging beef cattle from 2007 onwards, the regional designations were revised based on data available from the NAHMS 2007 through 2008 survey on cow-calf system management practices (USDA:APHIS:VS 2010) and are shown in Table A-136. The data for each of the diets (e.g., proportions of different feed constituents, such as hay or grains) were used to determine feed chemical composition for use in estimating DE and Y_m for each animal type.

Table A-135: Regions used for Characterizing the Diets of Dairy Cattle (all years) and Foraging Cattle from 1990–2006

West	California	Northern Great Plains	Midwestern	Northeast	Southcentral	Southeast
Alaska	California	Colorado	Illinois	Connecticut	Arkansas	Alabama
Arizona		Kansas	Indiana	Delaware	Louisiana	Florida
Hawaii		Montana	Iowa	Maine	Oklahoma	Georgia
Idaho		Nebraska	Michigan	Maryland	Texas	Kentucky
Nevada		North Dakota	Minnesota	Massachusetts		Mississippi
New Mexico		South Dakota	Missouri	New		North Carolina
Oregon		Wyoming	Ohio	Hampshire		South Carolina
Utah			Wisconsin	New Jersey		Tennessee
Washington				New York		Virginia
				Pennsylvania		
				Rhode Island		
				Vermont		
				West Virginia		

Source: USDA (1996).

Table A-136: Regions used for Characterizing the Diets of Foraging Cattle from 2007–2022

West	Central	Northeast	Southeast
Alaska	Illinois	Connecticut	Alabama
Arizona	Indiana	Delaware	Arkansas
California	Iowa	Maine	Florida
Colorado	Kansas	Maryland	Georgia
Hawaii	Michigan	Massachusetts	Kentucky
Idaho	Minnesota	New Hampshire	Louisiana
Montana	Missouri	New Jersey	Mississippi
Nevada	Nebraska	New York	North Carolina
New Mexico	North Dakota	Pennsylvania	Oklahoma
Oregon	Ohio	Rhode Island	South Carolina
Utah	South Dakota	Vermont	Tennessee
Washington	Wisconsin	West Virginia	Texas
Wyoming			Virginia

Note: States in **bold** represent a change in region from the 1990 to 2006 assessment. Region designations were updated to ensure the most accurate representation of foraging diets within each state for the 2007 to 2020 time period.

Source: Based on data from USDA:APHIS:VS (2010).

DE and Y_m vary by diet and animal type. The IPCC recommends Y_m values of 3.0 ± 1.0 percent for feedlot cattle and 6.5 ± 1.0 percent for all other cattle (IPCC 2006). Given the availability of detailed diet information for different regions and animal types in the United States, DE and Y_m values unique to the United States were developed for dairy and beef cattle. Digestible energy and Y_m values were estimated across the time series for each cattle population category based on physiological modeling, published values, and/or expert opinion.

For dairy cows, ruminant digestion models were used to estimate Y_m . The three major categories of input required by the models are animal description (e.g., cattle type, mature weight), animal performance (e.g., initial and final weight, age at start of period), and feed characteristics (e.g., chemical composition, habitat, grain or forage). Data used to simulate ruminant digestion is provided for a particular animal that is then used to represent a group of animals with similar characteristics. The Y_m values were estimated for 1990 using the Donovan and Baldwin model (1999), which represents physiological processes in the ruminant animals, as well as diet characteristics from USDA (1996). The Donovan and Baldwin model is able to account for differing diets (i.e., grain-based or forage-based), so that Y_m values for the variable feeding characteristics within the U.S. cattle population can be estimated. Subsequently, a literature review of dairy diets was conducted and nearly 250 diets were analyzed from 1990 through 2009 across 23 states—the review indicated highly variable diets, both temporally and spatially. Kebreab et al. (2008) conducted an evaluation of models and found that the COWPOLL model was the best model for estimating Y_m for dairy, so COWPOLL was used to determine the Y_m value associated with each of the evaluated diets. The statistical analysis of the resulting Y_m estimates showed a downward trend in predicting Y_m , which inventory team experts modeled using the following best-fit non-linear curve:

Equation A-22: Best Fit Curve for Estimating the Methane Conversion Rate for Dairy Cattle

$$Y_m = 4.52e^{\left(\frac{1.22}{year-1980}\right)}$$

The inventory team determined that the most comprehensive approach to estimating annual, region-specific Y_m values was to use the 1990 baseline Y_m values derived from Donovan and Baldwin and then scale these Y_m values for each year beyond 1990 with a factor based on this function. The scaling factor is the ratio of the Y_m value for the year in question to the 1990 baseline Y_m value. The scaling factor for each year was multiplied by the baseline Y_m value. The resulting Y_m equation (incorporating both Donovan and Baldwin (1999) and COWPOLL) is shown below (and described in ERG 2016):

Equation A-23: Scaling Factor for the Dairy Cattle Methane Conversion Rate

$$Y_{m=} Y_m (1990) EXP \left(\frac{1.22}{(Year-1980)} \right) / EXP \left(\frac{1.22}{(1990-1980)} \right)$$

DE values for dairy cows were estimated from the literature search based on the annual trends observed in the data collection effort. The regional variability observed in the literature search was not statistically significant, and therefore DE was not varied by region, but did vary over time, and was grouped by the following years 1990 through 1993, 1994 through 1998, 1999 through 2003, 2004 through 2006, 2007, and 2008 onwards.

Considerably less data was available for dairy heifers and dairy calves. Therefore, for dairy heifers assumptions were based on the relationship of the collected data in the literature on dairy heifers to the data on dairy cow diets. From this relationship, DE was estimated as the mature cow DE minus three percent, and Y_m was estimated as that of the mature dairy cow plus 0.1 percent.

To calculate the DE values for grazing beef cattle, diet composition assumptions were used to estimate weighted DE values for a combination of forage and supplemental diets. The forage portion makes up an estimated 85 to 95 percent of grazing beef cattle diets, and there is considerable variation of both forage type and quality across the United States. Currently there is no comprehensive survey of this data, so for this analysis two regional DE values were developed to account for the generally lower forage quality in the “West” region of the United States versus all other regions in Table A-135 (California, Northern Great Plains, Midwestern, Northeast, Southcentral, Southeast) and Table A-136 (Central, Northeast, and Southeast). For all non-western grazing cattle, the forage DE was an average of the estimated seasonal values for grass pasture diets for a calculated DE of 64.2 percent. For foraging cattle in the west, the forage DE was calculated as the seasonal average for grass pasture, meadow and range diets, for a calculated DE of 61.3 percent. The assumed specific components of each of the broad forage types, along with their corresponding DE value and the calculated regional DE values can be found in Table A-137. In addition, beef cattle are assumed to be fed a supplemental diet, consequently, two sets of supplemental diets were developed, one for 1990 through 2006 (Donovan 1999) and one for 2007 onwards (Preston 2010, Archibeque 2011, USDA:APHIS:VS 2010) as shown in Table A-138 and Table A-139 along with the percent of each total diet that is assumed to be made up of the supplemental portion. By weighting the calculated DE values from the forage and supplemental diets, the DE values for the composite diet were calculated.⁷⁹ These values are used for steer and heifer stockers and beef replacements. Finally, for mature beef cows and bulls, the DE value was adjusted downward by two percent to reflect the lower digestibility diets of mature cattle based on Johnson (2002). Y_m values for all grazing beef cattle were set at 6.5 percent based on Johnson (2002). The Y_m values and the resulting final weighted DE values by region for 2007 onwards are shown in Table A-140.

For feedlot animals, DE and Y_m are adjusted over time as diet compositions in actual feedlots are adjusted based on new and improved nutritional information and availability of feed types. Feedlot diets are assumed to not differ significantly by state, and therefore only a single set of national diet values is utilized for each year. The DE and Y_m values for 1990 were estimated by Dr. Don Johnson (1999). In the CEFM, the DE values for 1991 through 1999 were linearly extrapolated based on values for 1990 and 2000. DE and Y_m values from 2000 through the current year were estimated using the MOLLY model as described in Kebreab et al. (2008), based on a series of average diet feed compositions from Galyean and Gleghorn (2001) for 2000 through 2006 and Vasconcelos and Galyean (2007) for 2007 onwards. In addition, feedlot animals are assumed to spend the first 25 days in the feedlot on a “step-up” diet to become accustomed to the higher quality feedlot diets. The step-up DE and Y_m are calculated as the average of all state forage and feedlot diet DE and Y_m values.

For calves aged 4 through 6 months, a gradual weaning from milk is simulated, with calf diets at 4 months assumed to be 25 percent forage, increasing to 50 percent forage at age 5 months, and 75 percent forage at age 6 months. The portion of the diet allocated to milk results in zero emissions, as recommended by the IPCC (2006). For calves, the DE for the remainder of the diet is assumed to be similar to that of slightly older replacement heifers (both beef and dairy are calculated separately). The Y_m for beef calves is also assumed to be similar to that of beef replacement heifers (6.5 percent), as literature does not provide an alternative Y_m for use in beef calves. For dairy calves, the Y_m is assumed to be 7.8 percent at 4 months, 8.03 percent at 5 months, and 8.27 percent at 6 months based on estimates provided by Soliva (2006) for Y_m at 4 and 7 months of age and a linear interpolation for 5 and 6 months.

Table A-141 shows the regional DE and Y_m for U.S. cattle in each region for 2022.

⁷⁹ For example, the West has a forage DE of 61.3 which makes up 90 percent of the diet and a supplemented diet DE of 67.4 percent was used for 10 percent of the diet, for a total weighted DE of 61.9 percent, as shown in Table A-140.

Table A-137: Feed Components and Digestible Energy Values Incorporated into Forage Diet Composition Estimates

Forage Type	DE (% of GE)	Grass pasture - Spring	Grass pasture - Summer	Grass pasture - Fall	Range June	Range July	Range August	Range September	Range Winter	Meadow - Spring	Meadow - Fall
Bahiagrass <i>Paspalum notatum</i> , fresh	61.38			x							
Bermudagrass <i>Cynodon dactylon</i> , fresh	66.29		x								
Bremudagrass, Coastal <i>Cynodon dactylon</i> , fresh	65.53		x								
Bluegrass, Canada <i>Poa compressa</i> , fresh, early vegetative	73.99	x									
Bluegrass, Kentucky <i>Poa pratensis</i> , fresh, early vegetative	75.62	x									
Bluegrass, Kentucky <i>Poa pratensis</i> , fresh, mature	59.00		x	x							
Bluestem <i>Andropogon</i> spp, fresh, early vegetative	73.17				x						
Bluestem <i>Andropogon</i> spp, fresh, mature	56.82					x	x	x	x		x
Brome <i>Bromus</i> spp, fresh, early vegetative	78.57	x									
Brome, Smooth <i>Bromus inermis</i> , fresh, early vegetative	75.71	x									
Brome, Smooth <i>Bromus inermis</i> , fresh, mature	57.58		x	x					x		
Buffalograss, <i>Buchloe dactyloides</i> , fresh	64.02				x	x					
Clover, Alsike <i>Trifolium hybridum</i> , fresh, early vegetative	70.62	x									
Clover, Ladino <i>Trifolium repens</i> , fresh, early vegetative	73.22	x									
Clover, Red <i>Trifolium pratense</i> , fresh, early bloom	71.27	x									
Clover, Red <i>Trifolium pratense</i> , fresh, full bloom	67.44		x		x						
Corn, Dent Yellow <i>Zea mays indentata</i> , aerial part without ears, without husks, sun-cured, (stover)(straw)	55.28			x							
Dropseed, Sand <i>Sporobolus cryptandrus</i> , fresh, stem cured	64.69				x	x	x			x	
Fescue <i>Festuca</i> spp, hay, sun-cured, early vegetative	67.39	x									
Fescue <i>Festuca</i> spp, hay, sun-cured, early bloom	53.57			x							
Gramma <i>Bouteloua</i> spp, fresh, early vegetative	67.02	x									
Gramma <i>Bouteloua</i> spp, fresh, mature	63.38		x	x						x	
Millet, Foxtail <i>Setaria italica</i> , fresh	68.20	x			x						
Napiergrass <i>Pennisetum purpureum</i> , fresh, late bloom	57.24		x	x							

Forage Type	DE (% of GE)	Grass pasture - Spring	Grass pasture - Summer	Grass pasture - Fall	Range June	Range July	Range August	Range September	Range Winter	Meadow - Spring	Meadow - Fall
Needleandthread <i>Stipa comata</i> , fresh, stem cured	60.36					x	x	x			
Orchardgrass <i>Dactylis glomerata</i> , fresh, early vegetative	75.54	x									
Orchardgrass <i>Dactylis glomerata</i> , fresh, midbloom	60.13		x								
Pearlmillet <i>Pennisetum glaucum</i> , fresh	68.04	x									
Prairie plants, Midwest, hay, sun-cured	55.53				x						x
Rape <i>Brassica napus</i> , fresh, early bloom	80.88	x									
Rye <i>Secale cereale</i> , fresh	71.83	x									
Ryegrass, Perennial <i>Lolium perenne</i> , fresh	73.68	x									
Saltgrass <i>Distichlis</i> spp, fresh, post ripe	58.06		x	x							
Sorghum, Sudangrass <i>Sorghum bicolor sudanense</i> , fresh, early vegetative	73.27	x									
Squirreltail <i>Stanion</i> spp, fresh, stem-cured	62.00		x			x					
Summercypress, Gray <i>Kochia vestita</i> , fresh, stem-cured	65.11				x	x	x				
Timothy <i>Phleum pratense</i> , fresh, late vegetative	73.12	x									
Timothy <i>Phleum pratense</i> , fresh, midbloom	66.87		x								
Trefoil, Birdsfoot <i>Lotus corniculatus</i> , fresh	69.07	x									
Vetch <i>Vicia</i> spp, hay, sun-cured	59.44				x						
Wheat <i>Triticum aestivum</i> , straw	45.77				x						
Wheatgrass, Crested <i>Agropyron desertorum</i> , fresh, early vegetative	79.78	x									
Wheatgrass, Crested <i>Agropyron desertorum</i> , fresh, full bloom	65.89		x			x					
Wheatgrass, Crested <i>Agropyron desertorum</i> , fresh, post ripe	52.99			x					x		x
Winterfat, Common <i>Eurotia lanata</i> , fresh, stem-cured	40.89								x		
Weighted Average DE		72.99	62.45	57.26	67.11	62.70	60.62	58.59	52.07	64.03	55.11
Forage Diet for West	61.3	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
Forage Diet for All Other Regions	64.2	33.3%	33.3%	33.3%	-	-	-	-	-	-	-

Note: Forages marked with an x indicate that the DE from that specific forage type is included in the general forage type for that column (e.g., grass pasture, range, meadow or meadow by month or season).

Sources: Preston (2010) and Archibeque (2011).

Table A-138: DE Values with Representative Regional Diets for the Supplemental Diet of Grazing Beef Cattle for 1990–2006

Feed	Source of DE	Unweighted	California ^a	West	Northern	Southcentral	Northeast	Midwest	Southeast
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(NRC 1984)		DE (% of GE)		Great Plains					
Alfalfa Hay	Table 8, feed #006	61.79	65%	30%	30%	29%	12%	30%	
Barley		85.08	10%	15%					
Bermuda	Table 8, feed #030	66.29						35%	
Bermuda Hay	Table 8, feed #031	50.79				40%			
Corn	Table 8, feed #089	88.85	10%	10%	25%	11%	13%	13%	
Corn Silage	Table 8, feed #095	72.88			25%		20%	20%	
Cotton Seed Meal						7%			
Grass Hay	Table 8, feed #126, 170, 274	58.37		40%				30%	
Orchard	Table 8, feed #147	60.13						40%	
Soybean Meal Supplement		77.15		5%	5%			5%	
Sorghum	Table 8, feed #211	84.23						20%	
Soybean Hulls		66.86						7%	
Timothy Hay	Table 8, feed #244	60.51					50%		
Whole Cotton Seed		75.75	5%				5%		
Wheat Middlings	Table 8, feed #257	68.09			15%	13%			
Wheat	Table 8, feed #259	87.95	10%						
Weighted Supplement DE (%)			70.1	67.4	73.0	62.0	67.6	66.9	68.0
Percent of Diet that is Supplement									
			5%	10%	15%	10%	15%	10%	5%

^a Emissions are currently calculated on a state-by-state basis, but diets are applied by the regions shown in the table above. Source of representative regional diets: Donovan (1999).

Table A-139: DE Values and Representative Regional Diets for the Supplemental Diet of Grazing Beef Cattle for 2007–2022

Feed	Source of DE (NRC1984)	Unweighted DE (% of GE)	West ^a	Central ^a	Northeast ^a	Southeast ^a
Alfalfa Hay	Table 8, feed #006	61.79	65%	30%	12%	
Bermuda	Table 8, feed #030	66.29				20%
Bermuda Hay	Table 8, feed #031	50.79				20%
Corn	Table 8, feed #089	88.85	10%	15%	13%	10%
Corn Silage	Table 8, feed #095	72.88		35%	20%	
Grass Hay	Table 8, feed #126, 170, 274	58.37	10%			
Orchard	Table 8, feed #147	60.13				30%
Protein supplement (West)	Table 8, feed #082, 134, 225 ^b	81.01	10%			
Protein Supplement (Central and Northeast)	Table 8, feed #082, 134, 225 ^b	80.76		10%	10%	
Protein Supplement (Southeast)	Table 8, feed #082, 134, 101 ^b	77.89				10%
Sorghum	Table 8, feed #211	84.23		5%		10%
Timothy Hay	Table 8, feed #244	60.51			45%	
Wheat Middlings	Table 8, feed #257	68.09		5%		

Wheat	Table 8, feed #259	87.95	5%		
Weighted Supplement					
DE		67.4	73.1	68.9	66.6
Percent of Diet that is Supplement		10%	15%	5%	15%

^a Note that emissions are currently calculated on a state-by-state basis, but diets are applied by the regions shown in the table above.

^b Not in equal proportions.

Sources of representative regional diets: Donovan (1999), Preston (2010), Archibeque (2011), and USDA:APHIS:VS (2010).

Table A-140: Foraging Animal DE (% of GE) and Y_m Values for Each Region and Animal Type for 2007–2022

Animal Type	Data	West ^a	Central	Northeast	Southeast
Beef Repl. Heifers	DE ^b	61.9	65.6	64.5	64.6
	Y_m ^c	6.5%	6.5%	6.5%	6.5%
Beef Calves (4–6 mo)	DE	61.9	65.6	64.5	64.6
	Y_m	6.5%	6.5%	6.5%	6.5%
Steer Stockers	DE	61.9	65.6	64.5	64.6
	Y_m	6.5%	6.5%	6.5%	6.5%
Heifer Stockers	DE	61.9	65.6	64.5	64.6
	Y_m	6.5%	6.5%	6.5%	6.5%
Beef Cows	DE	59.9	63.6	62.5	62.6
	Y_m	6.5%	6.5%	6.5%	6.5%
Bulls	DE	59.9	63.6	62.5	62.6
	Y_m	6.5%	6.5%	6.5%	6.5%

^a Note that emissions are currently calculated on a state-by-state basis, but diets are applied by the regions shown in the table above. To see the regional designation per state, please see Table A-136.

^b DE is the digestible energy in units of percent of GE (MJ/Day).

^c Y_m is the methane conversion rate, the fraction of GE in feed converted to methane.

Table A-141: Regional DE (% of GE) and Y_m Rates for Dairy and Feedlot Cattle by Animal Type for 2022

Animal Type	Data	Northern						
		California ^a	West	Great Plains	Southcentral	Northeast	Midwest	Southeast
Dairy Repl. Heifers	DE ^b	63.7	63.7	63.7	63.7	63.7	63.7	63.7
	Y_m ^c	5.5%	5.5%	5.2%	5.9%	5.8%	5.2%	6.4%
Dairy Calves (4–6 mo)	DE	63.7	63.7	63.7	63.7	63.7	63.7	63.7
	Y_m	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%
Dairy Cows	DE	66.7	66.7	66.7	66.7	66.7	66.7	66.7
	Y_m	5.4%	5.4%	5.1%	5.8%	5.7%	5.1%	6.3%
Steer Feedlot	DE	82.5	82.5	82.5	82.5	82.5	82.5	82.5
	Y_m	3.9%	3.9%	3.9%	3.9%	3.9%	3.9%	3.9%
Heifer Feedlot	DE	82.5	82.5	82.5	82.5	82.5	82.5	82.5
	Y_m	3.9%	3.9%	3.9%	3.9%	3.9%	3.9%	3.9%

^a Emissions are currently calculated on a state-by-state basis, but diets are applied in Table A-135 by the regions shown in the table above. To see the regional designation for foraging cattle per state, please see Table A-135.

^b DE is the digestible energy in units of percent of GE (MJ/Day).

^c Y_m is the methane conversion rate, the fraction of GE in feed converted to methane.

Step 3: Estimate CH₄ Emissions from Cattle

Emissions by state were estimated in three steps: a) determine gross energy (GE) intake using the Tier 2 IPCC (2006) equations, b) determine an emission factor using the GE values, Y_m and a conversion factor, and c) sum the daily

emissions for each animal type. Finally, the state emissions were aggregated to obtain the national emissions estimate. The necessary data values for each state and animal type include:

- Body Weight (kg)
- Weight Gain (kg/day)
- Net Energy for Activity (C_a , MJ/day)⁸⁰
- Standard Reference Weight (kg)⁸¹
- Milk Production (kg/day)
- Milk Fat (percent of fat in milk)⁸²
- Pregnancy (percent of population that is pregnant)
- DE (percent of GE intake digestible)
- Y_m (the fraction of GE converted to CH₄)
- Population

Step 3a: Determine Gross Energy, GE

As shown in the following equation, GE is derived based on the net energy estimates and the feed characteristics. Only variables relevant to each animal category are used (e.g., estimates for feedlot animals do not require the NE_l factor). All net energy equations are provided in IPCC (2006). Calculated GE values for 2022 are shown by state and animal type in Table A-142.

Equation A-24: Gross Energy Calculation for Enteric Fermentation

$$GE = \left[\frac{\left(\frac{NE_m + NE_a + NE_l + NE_{work} + NE_p}{REM} \right) + \left(\frac{NE_g}{REG} \right)}{\frac{DE\%}{100}} \right]$$

where,

GE	=	Gross energy (MJ/day)
NE_m	=	Net energy required by the animal for maintenance (MJ/day)
NE_a	=	Net energy for animal activity (MJ/day)
NE_l	=	Net energy for lactation (MJ/day)
NE_{work}	=	Net energy for work (MJ/day)
NE_p	=	Net energy required for pregnancy (MJ/day)
REM	=	Ratio of net energy available in a diet for maintenance to digestible energy consumed
NE_g	=	Net energy needed for growth (MJ/day)
REG	=	Ratio of net energy available for growth in a diet to digestible energy consumed
DE	=	Digestible energy expressed as a percent of gross energy (percent)

⁸⁰ Zero for feedlot conditions, 0.17 for high quality confined pasture conditions, and 0.36 for extensive open range or hilly terrain grazing conditions. C_a factor for dairy cows is weighted to account for the fraction of the population in the region that grazes during the year (IPCC 2006).

⁸¹ Standard Reference Weight is the mature weight of a female animal of the animal type being estimated, used in the model to account for breed potential.

⁸² Average milk fat varies by year and is derived from USDA's Economic Research Service Dairy Data set (USDA 2022).

Table A-142: Calculated Annual GE by Animal Type and State, for 2022 (1,000 GJ)

State	Dairy		Dairy Replace-ment	Dairy Replace-ment	Bulls	Beef		Beef Replace-ment	Beef Replace-ment	Steer Stockers	Heifer Stockers	Feedlot
	Calves	Cows	Heifers 7-11 Months	Heifers 12-23 Months		Calves	Beef Cows	Heifers 7-11 Months	Heifers 12-23 Months			
Alabama	13	315	27	97	3,583	3,076	54,157	1,254	3,584	1,071	1,178	339
Alaska	1	12	1	5	400	39	671	19	53	12	10	3
Arizona	867	30,365	1,600	5,817	1,779	845	14,712	313	890	7,115	635	13,234
Arkansas	22	523	40	145	4,582	4,142	72,935	1,568	4,480	2,621	1,696	654
California	7,684	267,756	10,132	36,838	5,336	3,360	58,503	1,441	4,095	15,702	5,711	26,806
Colorado	902	32,997	1,533	5,574	4,002	3,152	54,890	1,691	4,807	19,628	14,975	56,027
Conn.	83	2,871	127	460	42	21	364	23	67	23	35	9
Delaware	13	366	16	58	25	8	137	7	20	62	7	10
Florida	469	14,928	400	1,454	4,582	4,096	72,129	1,452	4,148	570	589	175
Georgia	371	12,507	333	1,212	2,499	2,229	39,248	1,161	3,318	912	589	227
Hawaii	4	47	13	48	356	391	6,814	138	392	221	127	49
Idaho	2,913	104,999	4,666	16,965	3,558	2,460	42,845	1,190	3,383	7,851	5,711	15,456
Illinois	362	11,766	547	1,987	1,466	1,512	26,709	622	1,781	4,356	2,067	10,143
Indiana	831	28,740	800	2,908	1,303	820	14,497	396	1,134	2,134	1,033	5,071
Iowa	1,005	35,610	1,600	5,817	4,887	4,035	71,302	1,811	5,182	28,673	13,547	56,510
Kansas	755	26,265	2,133	7,755	6,923	6,336	111,956	3,055	8,745	45,343	39,264	126,060
Kentucky	197	6,371	467	1,696	4,999	4,421	77,851	1,452	4,148	5,015	2,591	869
Louisiana	40	984	40	145	2,499	2,064	36,346	929	2,655	524	448	147
Maine	116	3,765	173	630	125	46	808	47	133	103	71	26
Maryland	183	5,809	347	1,260	292	193	3,394	105	300	286	142	386
Mass.	42	1,360	73	267	84	37	647	35	100	57	24	12
Michigan	1,939	73,527	2,026	7,368	1,222	428	7,564	260	745	3,845	1,033	7,728
Minn.	2,055	69,972	2,800	10,179	2,443	1,605	28,363	962	2,753	10,891	3,329	18,354
Miss.	31	796	67	242	3,249	2,188	38,522	1,057	3,020	1,185	895	315
Missouri	308	7,975	400	1,454	8,959	8,655	152,925	3,395	9,717	9,335	5,281	3,864
Montana	49	1,637	53	194	8,449	6,418	111,758	4,009	11,394	5,152	4,721	2,077
Nebraska	259	9,222	400	1,454	8,959	8,035	141,974	3,961	11,337	56,679	36,279	136,202
Nevada	138	4,926	120	436	1,156	1,205	20,992	476	1,353	859	711	145
N. Hamp.	47	1,545	80	291	42	18	323	14	40	34	19	8
N. Jersey	19	616	37	136	58	36	630	17	50	50	28	12
N. Mexico	1,305	46,404	1,666	6,059	2,224	2,238	38,973	877	2,493	2,454	1,777	594
New York	2,770	99,219	4,399	15,995	1,671	459	8,082	466	1,331	1,029	945	1,063

State	Dairy		Dairy Replacement	Dairy Replacement	Beef			Beef Replacement	Beef Replacement	Steer	Heifer	Feedlot
	Calves	Cows	Heifers 7-11 Months	Heifers 12-23 Months	Bulls	Calves	Beef Cows	Heifers 7-11 Months	Heifers 12-23 Months	Stockers	Stockers	
N. Car.	174	6,087	187	679	2,583	1,652	29,093	720	2,057	957	612	238
N. Dakota	67	2,261	107	388	4,887	4,169	73,666	2,060	5,895	6,890	5,281	1,884
Ohio	1,108	36,675	1,600	5,817	2,443	1,391	24,582	736	2,105	4,890	1,378	7,245
Oklahoma	174	5,190	267	969	14,163	9,708	170,933	4,645	13,273	23,022	12,720	15,214
Oregon	558	17,904	733	2,666	3,558	2,495	43,447	1,253	3,561	4,171	3,046	6,279
Penn.	2,100	67,959	2,600	9,452	1,671	872	15,355	594	1,697	3,201	1,158	3,381
R. Island	2	70	7	24	8	5	89	2	7	7	5	2
S. Car.	40	1,206	67	242	1,000	723	12,733	337	962	251	212	70
S. Dakota	760	25,851	533	1,939	8,552	7,134	126,059	4,187	11,984	16,670	11,366	21,493
Tenn.	121	3,661	267	969	4,999	4,087	71,968	1,394	3,982	3,077	2,002	769
Texas	2,792	101,386	3,199	11,633	27,494	20,253	356,615	8,245	23,560	59,949	39,808	141,515
Utah	424	14,525	733	2,666	2,046	1,630	28,391	877	2,493	2,208	1,523	1,014
Vermont	536	17,537	693	2,520	251	69	1,212	52	150	114	154	40
Virginia	317	10,213	467	1,696	3,166	2,742	48,274	1,034	2,953	3,396	1,625	821
Wash.	1,166	40,710	1,733	6,301	1,601	1,107	19,272	689	1,958	4,662	3,300	10,626
W. Virg.	22	597	27	97	1,170	863	15,193	350	998	892	520	193
Wisconsin	5,696	203,876	8,799	31,991	2,443	1,315	23,242	962	2,753	8,891	1,952	13,041
Wyoming	40	1,464	67	242	3,113	3,365	58,589	1,817	5,163	3,926	3,426	3,333

Step 3b: Determine Emission Factor

The daily emission factor (DayEmit) was determined using the GE value and the methane conversion factor (Y_m) for each category. This relationship is shown in the following equation:

Equation A-25: Daily Emission Factor for Enteric Fermentation Based on Gross Energy Intake and Methane Conversion Factor

$$DayEmit = \frac{GE \times Y_m}{55.65}$$

where,

- DayEmit = Emission factor (kg CH₄/head/day)
- GE = Gross energy intake (MJ/head/day)
- Y_m = CH₄ conversion rate, which is the fraction of GE in feed converted to CH₄ (%)
- 55.65 = A factor for the energy content of methane (MJ/kg CH₄)

The daily emission factors were estimated for each animal type and state. Calculated annual national emission factors are shown by animal type in Table A-143. State-level emission factors are shown by animal type for 2022 in Table A-144.

Table A-143: Calculated Annual National Enteric Fermentation Emission Factors for Cattle by Animal Type (kg CH₄/head/year)

Cattle Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Dairy										
Calves	12	12	12	12	12	12	12	12	12	12
Cows	121	122	129	130	138	147	148	150	151	151
Replacements 7–11 months	48	46	46	45	46	46	45	45	45	45
Replacements 12–23 months	73	69	70	67	69	69	69	69	69	68
Beef										
Calves	11	11	11	11	11	11	11	11	11	11
Bulls	91	94	94	97	98	98	98	98	98	98
Cows	88	91	90	93	94	94	94	95	95	95
Replacements 7–11 months	54	57	56	59	60	60	60	60	60	60
Replacements 12–23 months	63	66	66	68	70	70	70	70	70	70
Steer Stockers	55	57	58	58	58	58	58	58	58	58
Heifer Stockers	52	56	60	60	60	60	60	60	60	60
Feedlot Cattle	39	38	39	39	42	43	43	43	44	44

Note: To convert to a daily emission factor, the yearly emission factor can be divided by 365 (the number of days in a year).

Table A-144: Enteric Fermentation Emission Factors for Cattle by Animal Type and State, for 2022 (kg CH₄/head/year)

State	Dairy		Dairy Replacement	Dairy Replacement	Bulls	Beef		Beef Replacement	Beef Replacement	Steer Stockers	Heifer Stockers	Feedlot
	Calves	Cows	Heifers 7-11 Months	Heifers 12-23 Months		Heifers 7-11 Months	Heifers 12-23 Months					
Alabama	12	119	53	80	97	11	94	60	69	58	60	33
Alaska	12	57	45	69	104	11	100	65	74	62	65	32
Arizona	12	152	45	69	104	11	100	65	74	62	65	34
Arkansas	12	109	49	74	97	11	94	60	69	58	60	32
California	12	151	45	69	104	11	100	65	74	62	65	33
Colorado	12	150	43	65	104	11	100	65	74	62	65	34
Conn.	12	160	48	73	98	11	94	60	69	58	60	33
Delaware	12	134	48	73	98	11	94	60	69	58	60	34
Florida	12	161	53	80	97	11	94	60	69	58	60	31
Georgia	12	170	53	80	97	11	94	60	69	58	60	33
Hawaii	12	57	45	69	104	11	100	65	74	62	65	32
Idaho	12	156	45	69	104	11	100	65	74	62	65	34
Illinois	12	133	43	65	95	10	92	58	68	56	58	33
Indiana	12	142	43	65	95	10	92	58	68	56	58	33
Iowa	12	145	43	65	95	10	92	58	68	56	58	33
Kansas	12	143	43	65	95	10	92	58	68	56	58	33
Kentucky	12	164	53	80	97	11	94	60	69	58	60	33
Louisiana	12	114	49	74	97	11	94	60	69	58	60	32
Maine	12	149	48	73	98	11	94	60	69	58	60	32
Maryland	12	146	48	73	98	11	94	60	69	58	60	34
Mass.	12	147	48	73	98	11	94	60	69	58	60	34
Michigan	12	156	43	65	95	10	92	58	68	56	58	33
Minn.	12	140	43	65	95	10	92	58	68	56	58	33
Miss.	12	128	53	80	97	11	94	60	69	58	60	32
Missouri	12	106	43	65	95	10	92	58	68	56	58	32
Montana	12	137	43	65	104	11	100	65	74	62	65	32
Nebraska	12	146	43	65	95	10	92	58	68	56	58	34
Nevada	12	154	45	69	104	11	100	65	74	62	65	33
N. Hamp.	12	151	48	73	98	11	94	60	69	58	60	33
N. Jersey	12	151	48	73	98	11	94	60	69	58	60	34
N. Mexico	12	154	45	69	104	11	100	65	74	62	65	33
New York	12	165	48	73	98	11	94	60	69	58	60	33
N. Car.	12	176	53	80	97	11	94	60	69	58	60	33

N. Dakota	12	138	43	65	95	10	92	58	68	56	58	32
Ohio	12	136	43	65	95	10	92	58	68	56	58	33
Oklahoma	12	139	49	74	97	11	94	60	69	58	60	33
Oregon	12	139	45	69	104	11	100	65	74	62	65	35
Penn.	12	149	48	73	98	11	94	60	69	58	60	33
R. Island	12	143	48	73	98	11	94	60	69	58	60	33
S. Car.	12	151	53	80	97	11	94	60	69	58	60	32
S. Dakota	12	140	43	65	95	10	92	58	68	56	58	33
Tenn.	12	153	53	80	97	11	94	60	69	58	60	33
Texas	12	169	49	74	97	11	94	60	69	58	60	34
Utah	12	148	45	69	104	11	100	65	74	62	65	33
Vermont	12	150	48	73	98	11	94	60	69	58	60	34
Virginia	12	163	53	80	97	11	94	60	69	58	60	34
Wash.	12	151	45	69	104	11	100	65	74	62	65	33
W. Virg.	12	123	48	73	98	11	94	60	69	58	60	32
Wisconsin	12	147	43	65	95	10	92	58	68	56	58	34
Wyoming	12	149	43	65	104	11	100	65	74	62	65	33

Note: To convert to a daily emission factor, the yearly emission factor can be divided by 365 (the number of days in a year).

For quality assurance purposes, U.S. emission factors for each animal type were compared to estimates provided by the other Annex I member countries of the United Nations Framework Convention on Climate Change (UNFCCC) (the most recently available summarized results for Annex I countries are through 2012 only). Results, presented in Table A-145, indicate that U.S. emission factors are comparable to those of other Annex I countries. Results in Table A-145 are presented along with Tier I emission factors provided by IPCC (2006). Throughout the time series, beef cattle in the United States generally emit more enteric CH₄ per head than other Annex I countries, while dairy cattle in the United States generally emit comparable enteric CH₄ per head.

Table A-145: Annex I Countries' Implied Enteric Fermentation Emission Factors for Cattle by Year (kg CH₄/head/year)⁸³

Year	Dairy Cattle		Beef Cattle	
	United States Implied Emission Factor	Mean of Implied Emission Factors for Annex I countries (excluding U.S.)	United States Implied Emission Factor	Mean of Implied Emission Factors for Annex I countries (excluding U.S.)
1990	105	96	71	53
1991	105	97	71	53
1992	105	96	72	54
1993	104	97	72	54
1994	104	98	72	54
1995	104	98	72	54
1996	104	99	72	54
1997	104	100	72	54
1998	104	101	73	55
1999	108	102	72	55
2000	109	103	72	55
2001	108	104	72	55
2002	109	105	72	55
2003	109	106	73	55
2004	107	107	74	55
2005	108	109	74	55
2006	108	110	74	55
2007	112	111	74	55
2008	112	112	75	55
2009	112	112	75	56
2010	113	113	74	55
2011	113	113	74	55
2012	115	112	74	51
2013	115	NA	74	NA
2014	116	NA	74	NA
2015	115	NA	74	NA
2016	116	NA	74	NA
2017	117	NA	74	NA
2018	118	NA	74	NA
2019	119	NA	74	NA
2020	120	NA	74	NA
2021	122	NA	74	NA
2022	123	NA	74	NA
Tier I EFs For North America, from IPCC (2006)		121	53	

NA (Not Applicable)

⁸³ Excluding calves.

Step 3c: Estimate Total Emissions

Emissions were summed for each month and for each state population category using the daily emission factor for a representative animal and the number of animals in the category. The following equation was used:

Equation A-26: Total Enteric Fermentation Emissions Calculated from Daily Emissions Rate and Population

$$\text{Emissions}_{\text{state}} = \text{DayEmit}_{\text{state}} \times \text{Days/Month} \times \text{SubPop}_{\text{state}}$$

where,

- Emissions_{state} = Emissions for state during the month (kg CH₄)
- DayEmit_{state} = Emission factor for the subcategory and state (kg CH₄/head/day)
- Days/Month = Number of days in the month
- SubPop_{state} = Number of animals in the subcategory and state during the month

This process was repeated for each month, and the monthly totals for each state subcategory were summed to achieve an emission estimate for a state for the entire year and state estimates were summed to obtain the national total. The estimates for each of the 10 subcategories of cattle are listed in Table A-146 (in kt) and Table A-147 (in MMT CO₂ Eq.). The emissions for each subcategory were then aggregated to estimate total emissions from beef cattle and dairy cattle for the entire year.

Table A-146: Enteric Fermentation CH₄ Emissions from Cattle (kt)

Cattle Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Dairy	1,547	1,471	1,492	1,473	1,594	1,737	1,732	1,743	1,764	1,748
Calves (4–6 months)	62	59	59	54	57	59	59	59	60	60
Cows	1,214	1,156	1,182	1,167	1,253	1,385	1,383	1,398	1,424	1,417
Replacements 7–11 months	58	56	55	56	62	64	63	62	60	58
Replacements 12–23 months	212	201	196	196	222	230	227	225	221	212
Beef	4,742	5,396	5,050	4,986	4,963	5,042	5,062	5,018	5,010	4,891
Calves (4–6 months)	182	193	186	179	169	171	168	167	165	161
Bulls	196	225	215	214	215	221	221	219	217	207
Cows	2,862	3,199	3,037	3,035	2,955	2,972	2,994	2,963	2,919	2,383
Replacements 7–11 months	69	85	74	80	75	86	83	82	80	75
Replacements 12–23 months	188	241	204	217	213	240	232	227	227	214
Steer Stockers	563	662	509	473	476	442	449	440	445	445
Heifer Stockers	306	375	323	299	302	277	271	269	278	275
Feedlot Cattle	375	416	502	488	560	633	644	649	679	676
Total	6,289	6,866	6,541	6,460	6,557	6,779	6,794	6,761	6,774	6,639

Note: Totals may not sum due to independent rounding.

Table A-147: Enteric Fermentation CH₄ Emissions from Cattle (MMT CO₂ Eq.)

Cattle Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Dairy	43.3	41.2	41.8	41.3	44.6	48.6	48.5	48.8	49.4	48.9
Calves (4–6 months)	1.7	1.6	1.6	1.5	1.6	1.6	1.7	1.7	1.7	1.7
Cows	34.0	32.4	33.1	32.7	35.1	38.8	38.7	39.1	39.9	39.7
Replacements 7–11 months	1.6	1.6	1.5	1.6	1.7	1.8	1.8	1.7	1.7	1.6
Replacements 12–23 months	5.9	5.6	5.5	5.5	6.2	6.4	6.3	6.3	6.2	5.9
Beef	132.8	151.1	141.4	139.6	139.0	141.2	141.7	140.5	140.3	137.0
Calves (4–6 months)	5.1	5.4	5.2	5.0	4.7	4.8	4.7	4.7	4.6	4.5
Bulls	5.5	6.3	6.0	6.0	6.0	6.2	6.2	6.1	6.1	5.8
Cows	80.1	89.6	85.0	85.0	82.8	83.2	83.8	83.0	81.7	79.5
Replacements 7–11 months	1.9	2.4	2.1	2.3	2.1	2.4	2.3	2.3	2.2	2.1
Replacements 12–23 months	5.3	6.7	5.7	6.1	6.0	6.7	6.5	6.4	6.4	6.0
Steer Stockers	15.8	18.5	14.2	13.2	13.3	12.4	12.6	12.3	12.5	12.5
Heifer Stockers	8.6	10.5	9.1	8.4	8.4	7.7	7.6	7.5	7.8	7.7
Feedlot Cattle	10.5	11.6	14.0	13.7	15.7	17.7	18.0	18.2	19.0	18.9
Total	176.1	192.3	183.2	180.9	183.6	189.8	190.2	189.3	189.7	185.9

Note: Totals may not sum due to independent rounding.

Emission Estimates from Other Livestock

“Other livestock” include horses, sheep, swine, goats, American bison, and mules and asses. All livestock population data, except for American bison for years prior to 2002, were taken from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) agricultural statistics database (USDA 2023) or the Census of Agriculture (USDA 2019). The Manure Management Annex 3.11 discusses the methods for obtaining annual average populations and disaggregating into state data where needed and provides the resulting population data for the other livestock that were used for estimating all livestock-related emissions. For each animal category, the USDA publishes monthly, annual, or multi-year livestock population and production estimates. American bison estimates prior to 2002 were estimated using data from the National Bison Association (1999).

Methane emissions from swine, horses, mules and asses were estimated by multiplying national population estimates by the default IPCC emission factor (IPCC 2006). For sheep and goats, default national emission factors were updated to reflect revisions made in the *2019 Refinement to the 2006 IPCC Guidelines*, which best reflects values representative of the United States. The *2019 Refinement to the 2006 IPCC Guidelines* was released to clarify and elaborate on the existing guidance, along with providing updates to default values of emission factors and other parameters based on updated science. For American bison the emission factor for buffalo (IPCC 2006) was used and adjusted based on the ratio of live weights of 300 kg for buffalo (IPCC 2006) and 1,130 pounds (513 kg) for American Bison (National Bison Association 2011) to the 0.75 power. This methodology for determining emission factors is recommended by IPCC (2006) for animals with similar digestive systems. Table A-148 shows the emission factors used for these other livestock. National enteric fermentation emissions from all livestock types are shown in Table A-149 and Table A-150. Enteric fermentation emissions from most livestock types, broken down by state, for 2021 are shown in Table A-151 through Table A-154. Livestock populations are shown in Table A-124.

Table A-148: Enteric Fermentation Emission Factors for Other Livestock (kg CH₄/head/year)

Livestock Type	Emission Factor
Swine	1.5
Horses	18
Sheep	9
Goats	9
American Bison	82.2
Mules and Asses	10.0

Source: IPCC (2006), IPCC (2019), except American Bison, as described in text.

Table A-149: CH₄ Emissions from Enteric Fermentation (kt)

Livestock Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Beef Cattle	4,742	5,396	5,050	4,986	4,963	5,042	5,062	5,018	5,010	4,891
Dairy Cattle	1,547	1,471	1,492	1,473	1,594	1,737	1,732	1,743	1,764	1,748
Swine	81	88	88	92	97	110	115	115	111	110
Horses	40	47	61	70	68	48	46	43	40	37
Sheep	102	81	63	55	51	47	47	47	47	46
Goats	23	21	22	26	26	24	25	25	25	25
American Bison	4	9	16	17	15	15	16	16	17	17
Mules and Asses	1	1	1	2	3	3	3	3	3	3
Total	6,539	7,114	6,793	6,722	6,816	7,028	7,045	7,010	7,017	6,878

Note: Totals may not sum due to independent rounding.

Table A-150: CH₄ Emissions from Enteric Fermentation (MMT CO₂ Eq.)

Livestock Type	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Beef Cattle	132.8	151.1	141.4	139.6	139.0	141.2	141.7	140.5	140.3	137.0
Dairy Cattle	43.3	41.2	41.8	41.3	44.6	48.6	48.5	48.8	49.4	48.9
Swine	2.3	2.5	2.5	2.6	2.7	3.1	3.2	3.2	3.1	3.1
Horses	1.1	1.3	1.7	2.0	1.9	1.4	1.3	1.2	1.1	1.0
Sheep	2.9	2.3	1.8	1.5	1.4	1.3	1.3	1.3	1.3	1.3
Goats	0.6	0.6	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7
American Bison	0.1	0.2	0.4	0.5	0.4	0.4	0.4	0.5	0.5	0.5
Mules and Asses	+	+	+	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Total	183.1	199.2	190.2	188.2	190.8	196.8	197.3	196.3	196.5	192.6

+ Does not exceed 0.5 MMT CO₂ Eq.

Note: Totals may not sum due to independent rounding.

Table A-151: CH₄ Emissions from Enteric Fermentation from Cattle (MT), by State, for 2022

State	Dairy		Dairy	Dairy	Bulls	Beef		Beef	Beef	Steer Stockers	Heifer Stockers	Feedlot	Total
	Calves	Cows	Heifers 7-11 Months	Heifers 12-23 Months		Calves	Cows	Heifers 7-11 Months	Heifers 12-23 Months				
Alabama	19	356	31	111	4,184	3,592	63,256	1,465	4,186	1,251	1,376	331	80,159
Alaska	1	11	1	5	467	45	784	22	62	14	12	3	1,429
Arizona	1,237	29,484	1,582	5,752	2,078	987	17,184	366	1,040	8,311	741	12,516	81,277
Arkansas	32	545	42	154	5,352	4,838	85,189	1,831	5,232	3,062	1,981	644	108,903
California	10,966	259,992	10,020	36,432	6,233	3,924	68,333	1,683	4,783	18,341	6,670	25,549	452,925
Colorado	1,288	30,311	1,436	5,221	4,675	3,682	64,112	1,975	5,615	22,926	17,491	53,183	211,914
Conn.	118	2,952	133	482	49	24	425	27	78	27	41	9	4,364
Delaware	18	376	17	61	29	9	160	8	23	72	8	10	793
Florida	669	16,866	459	1,669	5,352	4,785	84,248	1,696	4,845	666	688	178	122,120
Georgia	529	14,130	383	1,391	2,919	2,603	45,842	1,356	3,876	1,065	688	223	75,006
Hawaii	5	46	13	48	416	457	7,959	161	457	258	148	48	10,016
Idaho	4,157	101,954	4,614	16,778	4,155	2,874	50,044	1,390	3,951	9,170	6,670	14,515	220,273
Illinois	516	10,809	512	1,861	1,712	1,766	31,196	727	2,081	5,088	2,414	9,883	68,565
Indiana	1,186	26,401	749	2,724	1,522	958	16,932	463	1,324	2,492	1,207	4,941	60,900
Iowa	1,435	32,712	1,498	5,448	5,708	4,713	83,282	2,115	6,053	33,490	15,823	53,859	246,136
Kansas	1,078	24,127	1,998	7,263	8,086	7,401	130,766	3,569	10,215	52,961	45,861	120,687	414,011
Kentucky	281	7,198	536	1,947	5,839	5,164	90,931	1,696	4,845	5,857	3,026	839	128,158
Louisiana	57	1,027	42	154	2,919	2,411	42,453	1,085	3,101	612	523	147	54,533
Maine	166	3,871	181	659	146	54	944	54	155	120	83	26	6,460
Maryland	261	5,974	363	1,319	342	225	3,965	122	350	334	166	357	13,776
Mass.	61	1,398	77	279	98	43	755	41	117	67	28	11	2,973
Michigan	2,767	67,542	1,898	6,900	1,427	500	8,834	304	870	4,491	1,207	7,581	104,322
Minn.	2,933	64,277	2,622	9,533	2,854	1,875	33,129	1,124	3,216	12,721	3,889	17,709	155,881
Miss.	45	899	77	278	3,795	2,555	44,995	1,234	3,527	1,384	1,045	309	60,144
Missouri	440	7,326	375	1,362	10,465	10,109	178,619	3,965	11,350	10,904	6,168	3,898	244,980
Montana	70	1,503	50	182	9,869	7,496	130,535	4,682	13,309	6,018	5,514	2,087	181,316
Nebraska	370	8,472	375	1,362	10,465	9,385	165,828	4,626	13,241	66,202	42,374	128,521	451,220
Nevada	198	4,783	119	431	1,351	1,408	24,519	556	1,580	1,003	830	138	36,916
N. Hamp.	67	1,589	84	304	49	21	378	16	47	40	22	8	2,625
N. Jersey	27	633	39	142	68	42	736	20	58	59	33	11	1,869
N. Mexico	1,862	45,058	1,648	5,992	2,597	2,614	45,522	1,024	2,911	2,866	2,075	572	114,741
New York	3,953	102,028	4,603	16,736	1,952	536	9,439	544	1,555	1,202	1,104	1,013	144,665

N. Car.	249	6,877	214	779	3,017	1,930	33,981	841	2,403	1,118	715	231	52,356
N. Dakota	96	2,077	100	363	5,708	4,870	86,043	2,406	6,885	8,048	6,168	1,903	124,666
Ohio	1,581	33,689	1,498	5,448	2,854	1,625	28,712	859	2,459	5,712	1,609	6,905	92,951
Oklahoma	249	5,413	283	1,029	16,543	11,339	199,653	5,426	15,504	26,890	14,857	14,716	311,900
Oregon	797	17,385	725	2,637	4,155	2,914	50,747	1,463	4,159	4,872	3,557	5,715	99,127
Penn.	2,997	69,883	2,720	9,889	1,952	1,019	17,935	694	1,983	3,739	1,352	3,222	117,384
R. Island	3	72	7	25	10	6	104	3	8	8	6	2	253
S. Car.	57	1,362	77	278	1,168	845	14,873	393	1,124	293	248	69	20,786
S. Dakota	1,084	23,747	499	1,816	9,989	8,333	147,239	4,891	13,998	19,471	13,275	20,647	264,989
Tenn.	172	4,137	306	1,113	5,839	4,774	84,059	1,628	4,651	3,594	2,339	750	113,361
Texas	3,985	105,751	3,395	12,343	32,113	23,656	416,531	9,631	27,519	70,021	46,496	134,447	885,887
Utah	606	14,104	725	2,637	2,389	1,904	33,161	1,024	2,911	2,579	1,779	988	64,808
Vermont	765	18,034	725	2,637	293	80	1,416	61	175	134	179	38	24,538
Virginia	453	11,539	536	1,947	3,698	3,202	56,385	1,207	3,450	3,967	1,898	772	89,053
Wash.	1,664	39,530	1,714	6,232	1,870	1,293	22,510	805	2,287	5,445	3,854	10,343	97,546
W. Virg.	32	614	28	101	1,366	1,008	17,746	408	1,166	1,042	607	195	24,314
Wisconsin	8,129	187,281	8,240	29,962	2,854	1,536	27,147	1,124	3,216	10,385	2,280	12,213	294,367
Wyoming	57	1,345	62	227	3,636	3,930	68,433	2,122	6,031	4,585	4,002	3,187	97,618

Table A-152: CH₄ Emissions from Enteric Fermentation from Cattle (MMT CO₂ Eq.), by State, for 2022

State	Dairy				Beef			Beef		Steer Stockers	Heifer Stockers	Feedlot	Total
	Dairy Calves	Dairy Cows	Dairy Heifers 7-11 Months	Dairy Heifers 12-23 Months	Beef Calves	Beef Cows	Beef Heifers 7-11 Months	Beef Heifers 12-23 Months					
Alabama	0.001	0.015	0.001	0.003	0.136	0.103	1.832	0.047	0.129	0.034	0.035	0.008	2.344
Alaska	0.000	0.000	0.000	0.000	0.011	0.001	0.022	0.001	0.001	0.000	0.000	0.000	0.038
Arizona	0.035	0.836	0.043	0.154	0.058	0.031	0.545	0.011	0.029	0.221	0.013	0.329	2.305
Arkansas	0.001	0.016	0.001	0.004	0.169	0.136	2.409	0.059	0.163	0.086	0.055	0.017	3.116
California	0.305	7.225	0.282	1.021	0.175	0.105	1.841	0.051	0.140	0.497	0.178	0.671	12.490
Colorado	0.033	0.796	0.040	0.146	0.145	0.124	2.167	0.066	0.180	0.626	0.484	1.375	6.183
Conn.	0.003	0.085	0.004	0.014	0.001	0.001	0.015	0.001	0.002	0.001	0.001	0.000	0.128
Delaware	0.001	0.015	0.001	0.003	0.001	0.000	0.006	0.000	0.001	0.002	0.000	0.000	0.029
Florida	0.020	0.525	0.015	0.055	0.163	0.134	2.380	0.051	0.141	0.019	0.020	0.004	3.527
Georgia	0.014	0.383	0.013	0.047	0.087	0.077	1.366	0.035	0.098	0.032	0.024	0.007	2.183
Hawaii	0.000	0.001	0.000	0.001	0.012	0.012	0.212	0.005	0.013	0.008	0.004	0.001	0.269
Idaho	0.113	2.781	0.122	0.443	0.116	0.078	1.377	0.055	0.151	0.241	0.170	0.382	6.030
Illinois	0.014	0.306	0.016	0.057	0.053	0.055	0.973	0.023	0.064	0.174	0.069	0.302	2.106

Indiana	0.031	0.696	0.026	0.095	0.043	0.028	0.499	0.016	0.043	0.078	0.035	0.129	1.721
Iowa	0.038	0.872	0.040	0.146	0.160	0.131	2.329	0.056	0.154	0.945	0.461	1.615	6.947
Kansas	0.030	0.661	0.049	0.178	0.226	0.209	3.714	0.096	0.265	1.511	1.192	3.171	11.301
Kentucky	0.009	0.217	0.017	0.062	0.191	0.152	2.688	0.049	0.136	0.160	0.087	0.021	3.788
Louisiana	0.002	0.033	0.001	0.004	0.082	0.068	1.198	0.032	0.089	0.019	0.016	0.004	1.547
Maine	0.005	0.118	0.005	0.020	0.004	0.002	0.029	0.001	0.004	0.004	0.003	0.001	0.196
Maryland	0.007	0.173	0.010	0.037	0.010	0.007	0.124	0.004	0.012	0.009	0.006	0.008	0.408
Mass.	0.002	0.040	0.003	0.009	0.003	0.001	0.015	0.001	0.002	0.001	0.001	0.000	0.077
Michigan	0.075	1.843	0.061	0.223	0.040	0.013	0.239	0.009	0.024	0.127	0.025	0.201	2.881
Minn.	0.079	1.716	0.083	0.299	0.080	0.053	0.939	0.036	0.101	0.378	0.123	0.501	4.387
Miss.	0.001	0.032	0.002	0.008	0.106	0.072	1.269	0.035	0.098	0.043	0.034	0.009	1.710
Missouri	0.014	0.230	0.012	0.045	0.320	0.301	5.361	0.128	0.355	0.298	0.169	0.134	7.367
Montana	0.002	0.044	0.002	0.006	0.305	0.229	4.013	0.166	0.454	0.201	0.195	0.059	5.677
Nebraska	0.010	0.236	0.011	0.038	0.320	0.278	4.946	0.142	0.392	1.729	1.153	3.280	12.535
Nevada	0.005	0.130	0.004	0.013	0.044	0.040	0.700	0.019	0.051	0.032	0.028	0.004	1.070
N. Hamp.	0.002	0.046	0.003	0.009	0.001	0.001	0.011	0.001	0.001	0.001	0.001	0.000	0.076
N. Jersey	0.001	0.019	0.001	0.004	0.003	0.001	0.025	0.001	0.002	0.001	0.001	0.000	0.060
N. Mexico	0.058	1.419	0.052	0.188	0.087	0.077	1.349	0.034	0.093	0.080	0.068	0.017	3.523
New York	0.110	2.823	0.135	0.490	0.055	0.016	0.277	0.016	0.044	0.041	0.032	0.027	4.066
N. Car.	0.007	0.194	0.008	0.028	0.084	0.055	0.971	0.025	0.068	0.030	0.018	0.006	1.494
N. Dakota	0.003	0.057	0.003	0.010	0.186	0.144	2.561	0.070	0.193	0.200	0.177	0.057	3.660
Ohio	0.045	0.957	0.042	0.153	0.080	0.043	0.767	0.027	0.074	0.160	0.050	0.206	2.603
Oklahoma	0.007	0.155	0.008	0.029	0.463	0.313	5.552	0.146	0.402	0.753	0.418	0.421	8.665
Oregon	0.022	0.493	0.026	0.094	0.116	0.085	1.498	0.045	0.122	0.116	0.102	0.117	2.837
Penn.	0.085	1.996	0.108	0.391	0.055	0.033	0.581	0.024	0.065	0.101	0.044	0.125	3.606
R. Island	0.000	0.003	0.000	0.001	0.000	0.000	0.003	0.000	0.001	0.000	0.000	0.000	0.008
S. Car.	0.002	0.047	0.002	0.006	0.035	0.027	0.471	0.010	0.028	0.009	0.009	0.002	0.649
S. Dakota	0.022	0.495	0.016	0.057	0.293	0.258	4.589	0.138	0.381	0.516	0.354	0.544	7.663
Tenn.	0.005	0.132	0.011	0.039	0.163	0.135	2.393	0.049	0.136	0.116	0.067	0.021	3.267
Texas	0.102	2.697	0.111	0.404	0.954	0.678	12.031	0.315	0.868	1.975	1.222	3.647	25.004
Utah	0.017	0.401	0.019	0.067	0.073	0.057	1.006	0.036	0.099	0.064	0.051	0.026	1.916
Vermont	0.022	0.516	0.022	0.078	0.008	0.002	0.034	0.002	0.005	0.003	0.004	0.001	0.697
Virginia	0.013	0.335	0.014	0.051	0.109	0.093	1.648	0.037	0.101	0.123	0.050	0.024	2.598
Wash.	0.050	1.200	0.047	0.171	0.058	0.037	0.641	0.024	0.066	0.164	0.116	0.296	2.870
W. Virg.	0.001	0.020	0.001	0.004	0.041	0.030	0.525	0.013	0.037	0.033	0.017	0.005	0.729
Wisconsin	0.223	5.082	0.242	0.878	0.080	0.045	0.798	0.035	0.095	0.247	0.038	0.310	8.073
Wyoming	0.001	0.025	0.001	0.005	0.131	0.116	2.035	0.068	0.186	0.124	0.107	0.086	2.885

Table A-153: CH₄ Emissions from Enteric Fermentation from Other Livestock (metric tons), by State, for 2022

State	Swine	Horses	Sheep	Goats	American Bison	Mules and Asses	Total
Alabama	39	643	164	449	4	107	1,407
Alaska	2	24	6	9	118	0	160
Arizona	221	1,150	900	454	8	25	2,757
Arkansas	221	532	150	286	6	72	1,267
California	128	1,020	5,175	1,140	109	50	7,621
Colorado	803	1,526	3,870	567	946	60	7,771
Connecticut	4	96	52	60	46	10	269
Delaware	4	40	12	10	17	1	83
Florida	11	1,084	163	632	5	123	2,018
Georgia	60	599	165	618	1	116	1,559
Hawaii	11	72	181	175	7	3	448
Idaho	36	639	2,070	346	2,771	24	5,887
Illinois	7,969	435	477	368	59	48	9,357
Indiana	6,506	1,054	540	394	25	41	8,560
Iowa	35,138	710	1,440	960	241	30	38,518
Kansas	2,861	575	585	500	396	44	4,961
Kentucky	675	1,752	531	500	202	119	3,779
Louisiana	8	496	87	171	6	63	831
Maine	7	92	117	48	17	4	285
Maryland	36	479	155	152	4	22	849
Massachusetts	11	159	115	60	1	14	360
Michigan	1,808	727	783	283	291	37	3,929
Minnesota	12,938	493	1,008	350	222	33	15,043
Mississippi	270	401	111	331	24	82	1,219
Missouri	4,950	968	873	450	31	115	7,387
Montana	338	1,073	1,710	165	1,943	29	5,257
Nebraska	5,344	592	657	291	2,708	14	9,604
Nevada	0	104	540	48	0	4	697
New Hampshire	6	89	71	32	26	5	229
New Jersey	11	344	118	121	0	16	610
New Mexico	2	648	810	351	389	28	2,228
New York	56	847	720	221	97	28	1,968
North Carolina	12,263	642	261	442	18	122	13,747
North Dakota	233	244	558	77	1,208	8	2,328
Ohio	3,994	1,444	1,143	609	92	84	7,366
Oklahoma	3,203	1,659	468	940	70	183	6,522
Oregon	14	1,037	1,305	518	195	41	3,110
Pennsylvania	2,025	1,022	864	495	98	96	4,601
Rhode Island	2	28	15	9	-	1	56
South Carolina	237	575	84	384	1	65	1,346
South Dakota	3,124	656	2,115	173	2,173	22	8,262
Tennessee	420	1,392	441	936	29	203	3,421
Texas	1,699	4,779	6,300	7,172	875	1,002	21,827
Utah	1,208	844	2,430	217	79	10	4,788
Vermont	6	97	151	81	16	-	350
Virginia	435	798	648	424	35	83	2,423
Washington	26	734	450	285	81	29	1,605
West Virginia	8	369	288	250	11	41	966
Wisconsin	518	833	738	1,258	621	32	3,999

Wyoming 162 702 2,970 172 817 36 4,859

“-” Indicates there are no emissions, as there is no significant population of this animal type.

Table A-154: CH₄ Emissions from Enteric Fermentation from Other Livestock (MMT CO₂ Eq.), by State, for 2022

State	Swine	Horses	Sheep	Goats	American Bison	Mules and Asses	Total
Alabama	0.001	0.018	0.005	0.013	0.000	0.003	0.039
Alaska	0.000	0.001	0.000	0.000	0.003	0.000	0.004
Arizona	0.006	0.032	0.025	0.013	0.000	0.001	0.077
Arkansas	0.006	0.015	0.004	0.008	0.000	0.002	0.035
California	0.004	0.029	0.145	0.032	0.003	0.001	0.213
Colorado	0.022	0.043	0.108	0.016	0.026	0.002	0.218
Connecticut	0.000	0.003	0.001	0.002	0.001	0.000	0.008
Delaware	0.000	0.001	0.000	0.000	0.000	0.000	0.002
Florida	0.000	0.030	0.005	0.018	0.000	0.003	0.057
Georgia	0.002	0.017	0.005	0.017	0.000	0.003	0.044
Hawaii	0.000	0.002	0.005	0.005	0.000	0.000	0.013
Idaho	0.001	0.018	0.058	0.010	0.078	0.001	0.165
Illinois	0.223	0.012	0.013	0.010	0.002	0.001	0.262
Indiana	0.182	0.030	0.015	0.011	0.001	0.001	0.240
Iowa	0.984	0.020	0.040	0.027	0.007	0.001	1.079
Kansas	0.080	0.016	0.016	0.014	0.011	0.001	0.139
Kentucky	0.019	0.049	0.015	0.014	0.006	0.003	0.106
Louisiana	0.000	0.014	0.002	0.005	0.000	0.002	0.023
Maine	0.000	0.003	0.003	0.001	0.000	0.000	0.008
Maryland	0.001	0.013	0.004	0.004	0.000	0.001	0.024
Massachusetts	0.000	0.004	0.003	0.002	0.000	0.000	0.010
Michigan	0.051	0.020	0.022	0.008	0.008	0.001	0.110
Minnesota	0.362	0.014	0.028	0.010	0.006	0.001	0.421
Mississippi	0.008	0.011	0.003	0.009	0.001	0.002	0.034
Missouri	0.139	0.027	0.024	0.013	0.001	0.003	0.207
Montana	0.009	0.030	0.048	0.005	0.054	0.001	0.147
Nebraska	0.150	0.017	0.018	0.008	0.076	0.000	0.269
Nevada	0.000	0.003	0.015	0.001	0.000	0.000	0.020
New Hampshire	0.000	0.002	0.002	0.001	0.001	0.000	0.006
New Jersey	0.000	0.010	0.003	0.003	0.000	0.000	0.017
New Mexico	0.000	0.018	0.023	0.010	0.011	0.001	0.062
New York	0.002	0.024	0.020	0.006	0.003	0.001	0.055
North Carolina	0.343	0.018	0.007	0.012	0.000	0.003	0.385
North Dakota	0.007	0.007	0.016	0.002	0.034	0.000	0.065
Ohio	0.112	0.040	0.032	0.017	0.003	0.002	0.206
Oklahoma	0.090	0.046	0.013	0.026	0.002	0.005	0.183
Oregon	0.000	0.029	0.037	0.014	0.005	0.001	0.087
Pennsylvania	0.057	0.029	0.024	0.014	0.003	0.003	0.129
Rhode Island	0.000	0.001	0.000	0.000	-	0.000	0.002
South Carolina	0.007	0.016	0.002	0.011	0.000	0.002	0.038
South Dakota	0.087	0.018	0.059	0.005	0.061	0.001	0.231
Tennessee	0.012	0.039	0.012	0.026	0.001	0.006	0.096
Texas	0.048	0.134	0.176	0.201	0.025	0.028	0.611
Utah	0.034	0.024	0.068	0.006	0.002	0.000	0.134
Vermont	0.000	0.003	0.004	0.002	0.000	-	0.010
Virginia	0.012	0.022	0.018	0.012	0.001	0.002	0.068
Washington	0.001	0.021	0.013	0.008	0.002	0.001	0.045

West Virginia	0.000	0.010	0.008	0.007	0.000	0.001	0.027
Wisconsin	0.014	0.023	0.021	0.035	0.017	0.001	0.112
Wyoming	0.005	0.020	0.083	0.005	0.023	0.001	0.136

“-“ Indicates there are no emissions, as there is no significant population of this animal type.

“+” Indicates emissions fall below 0.00005 MMT CO₂ Eq.

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3.11. Methodology for Estimating CH₄ and N₂O Emissions from Manure Management⁸⁴

The following steps were used to estimate methane (CH₄) and nitrous oxide (N₂O) emissions from the management of livestock manure for the years 1990 through 2022.

Step 1: Livestock Population Characterization Data

Annual animal population data for 1990 through 2022 for all livestock types, except American bison, goats, horses, mules and asses were obtained from the USDA NASS. The population data used in the emissions calculations for cattle, swine, and sheep were downloaded from the USDA NASS Quick Stats Database (USDA 2023a). Poultry population data were obtained from USDA NASS reports (USDA 1995a, 1995b, 1998, 1999, 2004a, 2004b, 2009a, 2009b, 2009c, 2009d, 2010a, 2010b, 2011a, 2011b, 2012a, 2012b, 2013a, 2013b, 2014, 2015, 2016, 2017, 2018, 2019a, 2019b, 2019c, 2021a, 2021b, and 2023a, 2023b, and 2023c). Goat population data for 1992, 1997, 2002, 2007, 2012, and 2017 were obtained from the Census of Agriculture (USDA 2019d), as were horse, mule and ass population data for 1987, 1992, 1997, 2002, 2007, 2012, and 2017 and American bison population for 2002, 2007, 2012, and 2017. American bison population data for 1990-1999 were obtained from the National Bison Association (1999). Additional data sources used and adjustments to these data sets are described below.

Cattle: For all cattle groups (cows, heifers, steers, bulls, and calves), the USDA data provide cattle inventories from January (for each state) and July (as a U.S. total only) of each year. Cattle inventories change over the course of the year, sometimes significantly, as new calves are born and as cattle are moved into feedlots and subsequently slaughtered; therefore, to develop the best estimate for the annual animal population, the populations and the individual characteristics, such as weight and weight gain, pregnancy, and lactation of each animal type were tracked in the Cattle Enteric Fermentation Model (CEFM—see section 5.1). For animals that have relatively static populations throughout the year, such as mature cows and bulls, the January 1 values were used. For animals that have fluctuating populations throughout the year, such as calves and growing heifers and steer, the populations are modeled based on a transition matrix that uses annual population data from USDA along with USDA data on animal births, placement into feedlots, and slaughter statistics.

Swine: The USDA provides quarterly data for each swine subcategory: breeding, market under 50 pounds (under 23 kg), market 50 to 119 pounds (23 to 54 kg), market 120 to 179 pounds (54 to 81 kg), and market 180 pounds and over (greater than 82 kg). The average of the quarterly data was used in the emission calculations. For states where only the December data is reported, the December data were used directly.

Sheep: The USDA provides total state-level data annually for lambs and sheep. Population distribution data for lambs and sheep on feed are not available after 1993 (USDA 1994). The number of lambs and sheep on feed for 1994 through 2022 were calculated using the average of the percent of lambs and sheep on feed from 1990 through 1993. In addition, all of the sheep and lambs “on feed” are not necessarily on “feedlots;” they may be on pasture/crop residue supplemented by feed. Data for those animals on feed that are in feedlots versus pasture/crop residue were provided only for lamb in 1993. To calculate the populations of sheep and lambs in feedlots for all years, it was assumed that the percentage of sheep and lambs on feed that are in feedlots versus pasture/crop residue is the same as that for lambs in 1993 (Anderson 2000).

Goats: Annual goat population data by state were available for 1992, 1997, 2002, 2007, 2012, and 2017 (USDA 2019d). The data for 1992 were used for 1990 through 1992. Data for 1993 through 1996, 1998 through 2001, 2003 through

⁸⁴ Note that direct N₂O emissions from dung and urine spread onto fields either directly as daily spread or after it is removed from manure management systems (e.g., lagoon, pit, etc.) and from livestock dung and urine deposited on pasture, range, or paddock lands are accounted for and discussed in the Agricultural Soil Management source category within the Agriculture Chapter. Indirect N₂O emissions dung and urine spread onto fields after it is removed from manure management systems (e.g., lagoon, pit, etc.) and from livestock dung and urine deposited on pasture, range, or paddock lands are also included in the Agricultural Soil Management source category. EPA is aware that there are minor differences in the PRP manure N data used in Agricultural Soil Management and Manure Management across the time series which are reflected in CRT tables and will be updated in the subsequent Inventory.

2006, 2008 through 2011, and 2013 through 2016 were interpolated based on the 1992, 1997, 2002, 2007, 2012, and 2017 Census data. Data for 2018 through 2022 were extrapolated based on 2017 Census data.

Horses: Annual horse population data by state were available for 1987, 1992, 1997, 2002, 2007, 2012, and 2017 (USDA 2019d). Data for 1990 through 1991, 1993 through 1996, 1998 through 2001, 2003 through 2006, 2008 through 2011, and 2013 through 2016 were interpolated based on the 1987, 1992, 1997, 2002, 2007, 2012, and 2017 Census data. Data for 2018 through 2022 were extrapolated based on 2017 Census data.

Mules and Asses: Annual mule and ass (burro and donkey) population data by state were available for 1987, 1992, 1997, 2002, 2007, 2012, and 2017 (USDA 2019d). Data for 1990 through 1991, 1993 through 1996, 1998 through 2001, 2003 through 2006, 2008 through 2011, and 2013 through 2016 were interpolated based on the 1987, 1992, 1997, 2002, 2007, 2012, and 2017 Census data. Data for 2018 through 2022 were extrapolated based on 2017 Census data.

American Bison: Annual American bison population data by state were available for 2002, 2007, 2012, and 2017 (USDA 2019d). Data for 1990 through 1999 were obtained from the Bison Association (1999). Data for 2000, 2001, 2003 through 2006, 2008 through 2011, and 2013 through 2016 were interpolated based on the Bison Association and 2002, 2007, 2012, and 2017 Census data. Data for 2018 through 2022 were extrapolated based on 2017 Census data.

Poultry: The USDA provides population data for hens (one year old or older), pullets (hens younger than one year old), other chickens, and production (slaughter) data for broilers and turkeys (USDA 1995a, 1995b, 1998, 1999, 2004a, 2004b, 2009b, 2009c, 2009d, 2009e, 2010a, 2010b, 2011a, 2011b, 2012a, 2012b, 2013a, 2013b, 2014, 2015, 2016, 2017, 2018, 2019a, 2019b, 2021a, 2021b, 2023a, 2023b, and 2023c). All poultry population data were adjusted to account for states that report non-disclosed populations to USDA NASS. The combined populations of the states reporting non-disclosed populations are reported as “other” states. State populations for the non-disclosed states were estimated by using Census of Agriculture data to provide a ratio of the non-disclosed state population to the “other” states’ total population (ERG 2021).

Because only production data are available for broilers and turkeys, population data are calculated by dividing the number of animals produced by the number of production cycles per year, or the turnover rate. Based on personal communications with John Lange, an agricultural statistician with USDA NASS, the broiler turnover rate ranges from 3.4 to 5.5 over the course of the inventory (Lange 2000). For turkeys, the turnover rate ranges from 2.4 to 3.0. A summary of the livestock population characterization data used to calculate CH₄ and N₂O emissions is presented in Table A-155.

Step 2: Waste Characteristics Data

Methane and N₂O emissions calculations are based on the following animal characteristics for each relevant livestock population:

- Volatile solids (VS) excretion rate;
- Maximum methane producing capacity (B₀) for U.S. animal waste;
- Nitrogen excretion rate (N_{ex}); and
- Typical animal mass (TAM).

Table A-156 presents a summary of the waste characteristics used in the emissions estimates. Published sources were reviewed for U.S.-specific livestock waste characterization data that would be consistent with the animal population data discussed in Step 1. The USDA’s Agricultural Waste Management Field Handbook (AWMFH; USDA 1996, 2008) is one of the primary sources of waste characteristics for non-cattle animal groups. Data from the 1996 and 2008 USDA AWMFH were used to estimate VS and N_{ex} for most non-cattle animal groups across the time series of the *Inventory*, as shown in Table A-157 (ERG 2010b and 2010c). The 1996 AWMFH data were based on measured values from U.S. farms; the 2008 AWMFH data were developed using the calculation method created by the American Society of Agricultural and Biological Engineers (ASABE), which is based on U.S. animal dietary intake and performance measures. Since the values from each of the two AWMFHs result from different estimation methods and reflect changes in animal genetics and nutrition over time, both data sources were used to create a time series across the *Inventory* as neither value would be appropriate to use across the entire span of *Inventory* years. Expert sources (USDA NRCS staff) agreed interpolating the two data sources across the time series would be appropriate as each methodology reflect the best available for that time period and the more recent data may not appropriately reflect the historic time series (ERG 2010b). Although the AWMFH values are lower than the IPCC (2006) values, these values are more appropriate for U.S. systems because they have been calculated using U.S.-specific data. Animal-specific notes about VS and N_{ex} are presented below:

- *Swine*: The VS and Nex data for breeding swine are from a combination of the types of animals that make up this animal group, namely gestating and farrowing swine and boars. It is assumed that a group of breeding swine is typically broken out as 80 percent gestating sows, 15 percent farrowing swine, and 5 percent boars (Safley 2000). Differing trends in VS and Nex values are due to the updated Nex calculation method from 2008 AWMFH. VS calculations did not follow the same procedure and were updated based on a fixed ratio of VS to total solids and past ASABE standards (ERG 2010b).
- *Poultry*: Due to the change in USDA reporting of hens and pullets in 2005, new nitrogen and VS excretion rates were calculated for the combined population of hens and pullets; a weighted average rate was calculated based on hen and pullet population data from 1990 to 2004.
- *Goats, Sheep, Horses, Mules and Asses*: In cases where data were not available in the USDA documents, data from the American Society of Agricultural Engineers, Standard D384.1 (ASAE 1998) or the *2006 IPCC Guidelines* were used.

The method for calculating VS excretion and Nex for cattle (including American bison, beef and dairy cows, bulls, heifers, and steers) is based on the relationship between animal performance characteristics such as diet, lactation, and weight gain and energy utilization. The method used is outlined by the IPCC (2019) Tier 2 methodology, and is modeled using the CEFM as described in the enteric fermentation portion of the inventory (documented in Moffroid and Pape 2013) in order to take advantage of the detailed diet and animal performance data assembled as part of the Tier II analysis for cattle. For American bison, VS and Nex were assumed to be the same as beef NOF bulls. The *2019 Refinements* offer updated clarity and guidance for several parameters (e.g., emission factors) and methodologies and, where appropriate, EPA is reviewing and applying to reflect the updated science.

The VS content of manure is the fraction of the diet consumed by cattle that is not digested and thus excreted as fecal material; fecal material combined with urinary excretions constitutes manure. The CEFM uses the input of digestible energy (DE) and the energy requirements of cattle to estimate gross energy (GE) intake and enteric CH₄ emissions. GE and DE are used to calculate the indigestible energy per animal as gross energy minus digestible energy plus the amount of gross energy for urinary energy excretion per animal (2 or 4 percent). This value is then converted to VS production per animal using the typical conversion of dietary gross energy to dry organic matter of 18.45 MJ/kg, after subtracting out the ash content of manure. The current equation recommended by the *2006 IPCC Guidelines* is:

Equation A-27: VS Production for Cattle

$$\text{VS production (kg)} = [(\text{GE} - \text{DE}) + (\text{UE} \times \text{GE})] \times \frac{1 - \text{ASH}}{18.45}$$

where,

GE	=	Gross energy intake (MJ)
DE	=	Digestible energy (MJ)
(UE × GE)	=	Urinary energy expressed as fraction of GE, assumed to be 0.04 except for feedlots which are reduced 0.02 as a result of the high grain content of their diet.
ASH	=	Ash content of manure calculated as a fraction of the dry matter feed intake (assumed to be 0.08 consistent with Equation 10.24, Volume 4, Chapter 10, of the <i>2006 IPCC Guidelines</i>).
18.45	=	Conversion factor for dietary GE per kg of dry matter (MJ per kg). This value is relatively constant across a wide range of forage and grain-based feeds commonly consumed by livestock.

Total nitrogen ingestion in cattle is determined by dietary protein intake. When feed intake of protein exceeds the nutrient requirements of the animal, the excess nitrogen is excreted, primarily through the urine. To calculate the nitrogen excreted by each animal type, the CEFM utilizes the energy balance calculations recommended by the *2006 IPCC Guidelines* for gross energy and the energy required for growth along with inputs of weight gain, milk production, and the percent of crude protein in the diets. The total nitrogen excreted is measured in the CEFM as nitrogen consumed minus nitrogen retained by the animal for growth and in milk. The basic equation for calculating Nex is shown below, followed by the equations for each of the constituent parts, based on the 10th Corrigenda for the *2006 IPCC Guidelines* (IPCC 2018).

Equation A-28: Nex Rates for Cattle

$$Nex_{(T)} = N_{intake} \times (1 - N_{retention_fract(T)})$$

where,

$Nex_{(T)}$	=	Annual N excretion rates (kg N animal ⁻¹ yr ⁻¹)
$N_{intake(T)}$	=	The annual N intake per head of animal of species/category T (kg N animal ⁻¹ yr ⁻¹)
$N_{retention(T)}$	=	Fraction of annual N intake that is retained by animal

N intake is estimated as:

Equation A-29: Daily Nitrogen Intake for Cattle

$$N_{intake(T)} = \frac{GE}{18.45} \times \left(\frac{CP\%}{6.25} \right)$$

where,

$N_{intake(T)}$	=	Daily N consumed per animal of category T (kg N animal ⁻¹ day ⁻¹)
GE	=	Gross energy intake of the animal based on digestible energy, milk production, pregnancy, current weight, mature weight, rate of weight gain, and IPCC constants (MJ animal ⁻¹ day ⁻¹)
18.45	=	Conversion factor for dietary GE per kg of dry matter (MJ kg ⁻¹)
CP%	=	Percent crude protein in diet, input
6.25	=	Conversion from kg of dietary protein to kg of dietary N (kg feed protein per kg N)

The portion of consumed N that is retained as product equals the nitrogen in milk plus the nitrogen required for weight gain. The N content of milk produced is calculated using milk production and percent protein, along with conversion factors. The nitrogen retained in body weight gain by stockers, replacements, or feedlot animals is calculated using the net energy for growth (NE_g), weight gain (WG), and other conversion factors and constants. The equation matches the 10th Corrigenda to the 2006 IPCC Guidelines (IPCC 2018), and is as follows:

Equation A-30: Nitrogen Retention from Milk and Body Weight for Cattle

$$N_{retention(T)} = \left[\frac{Milk \times \left(\frac{Milk\ PR\%}{100} \right)}{6.38} \right] + \left[\frac{WG \times \left[268 - \left(\frac{7.03 \times NE_g}{WG} \right) \right]}{1000 \times 6.25} \right]$$

where,

$N_{retention(T)}$	=	Daily N retained per animal of category T (kg N animal ⁻¹ day ⁻¹)
Milk	=	Milk production (kg animal ⁻¹ day ⁻¹)
268	=	Constant from 2019 IPCC Guidelines
7.03	=	Constant from 2019 IPCC Guidelines
NE _g	=	Net energy for growth, calculated in livestock characterization, based on current weight, mature weight, rate of weight gain, and IPCC constants, (MJ day ⁻¹)
1,000	=	Conversion from grams to kilograms (g kg ⁻¹)
6.25	=	Conversion from kg dietary protein to kg dietary N (kg protein per kg N)
Milk PR%	=	Percent of protein in milk (%)
6.38	=	Conversion from milk protein to milk N (kg protein per kg N)
WG	=	Weight gain, as input into the CEFM transition matrix (kg day ⁻¹)

The VS and N equations above were used to calculate VS and Nex rates for each state, animal type (heifers and steer on feed, heifers and steer not on feed, bulls and American bison), and year. Table A-158 presents the state-specific VS and Nex production rates used for cattle in 2022. As shown in Table A-158, the differences in the VS daily excretion and Nex rate trends between dairy cattle animal types is due to milk production. Milk production by cow varies from state to state and is used in calculating net energy for lactating, which is used to calculate VS and Nex for dairy cows. Milk

production is zero for dairy heifers (dairy heifers do not produce milk because they have not yet had a calf). Over time, the differences in milk production are also a big driver for the higher variability of VS and Nex rates in dairy cows.

Step 3: Waste Management System Usage Data

Table A-159 and Table A-160 summarize 2022 manure distribution data among waste management systems (WMS) at beef feedlots, dairies, dairy heifer facilities, and swine, layer, broiler, and turkey operations. Manure from the remaining animal types (beef cattle not on feed, American bison, goats, horses, mules and asses and sheep) is managed on pasture, range, or paddocks, on dry lot, or with solids storage systems. Note that the *Inventory* WMS estimates are based on state or regional WMS usage data and not built upon farm-level WMS estimates. Additional information on the development of the manure distribution estimates for each animal type is presented below. Definitions of each WMS type are presented in Table A-161.

Beef Cattle, Dairy Heifers and American Bison: The beef feedlot and dairy heifer WMS data were developed using regional information from EPA's Office of Water's engineering cost analyses conducted to support the development of effluent limitations guidelines for Concentrated Animal Feeding Operations (EPA 2002b). Based on EPA site visits and state contacts supporting this work and additional personal communication with the national USDA office to estimate the percent of beef steers and heifers in feedlots (Milton 2000), feedlot manure is almost exclusively managed in dry lots. In addition, there is a small amount of manure contained in runoff, which may or may not be collected in runoff ponds. Using EPA and USDA data and expert opinions (ERG assumptions documented in ERG 2000a), the runoff from feedlots was calculated by region in *Calculations: Percent Distribution of Manure for Waste Management Systems* and was used to estimate the percentage of manure managed in runoff ponds in addition to dry lots; this percentage ranges from 0.4 to 1.3 percent (ERG 2000a, 2023). For beef feedlot, these data were applied to 1990 through 2002. For 2018, WMS data were captured from a survey of NRCS regional staff (i.e., expert judgement). Data for 2019 through 2022 were assumed equal to 2018. WMS data for 2003 through 2017 were linearly interpolated consistent with IPCC time-series consistency techniques (ERG 2023). The remaining population categories of beef cattle outside of feedlots are managed through pasture, range, or paddock systems, which are utilized for the majority of the population of beef cattle in the country. American bison WMS data were assumed to be the same as beef cattle NOF.

Dairy Cows: The WMS data for dairy cows were developed using state and regional data from the Census of Agriculture, EPA's Office of Water, USDA, and the expert sources noted below. Farm-size distribution data are reported in the 1992, 1997, 2002, 2007, 2012, and 2017 Census of Agriculture (USDA 2019d). It was assumed that the Census data provided for 1992 were the same as that for 1990 and 1991, and data provided for 2017 were the same as that for 2018. Data for 1993 through 1996, 1998 through 2001, and 2003 through 2006, 2008 through 2011, and 2013 through 2016 were interpolated using the 1992, 1997, 2002, 2007, 2012, and 2017 Census data. The percent of waste by system was estimated using the USDA data broken out by geographic region and farm size.

For 1990 through 1996 the following methodology and sources were used to estimate dairy WMS:

Based on EPA site visits and the expert opinion of state contacts, manure from dairy cows at medium (200 through 700 head) and large (greater than 700 head) operations are managed using either flush systems or scrape/slurry systems (ERG 2000a). In addition, they may have a solids separator in place prior to their storage component. Estimates of the percent of farms that use each type of system (by geographic region) were developed by EPA's Office of Water and were used to estimate the percent of waste managed in lagoons (flush systems), liquid/slurry systems (scrape systems), and solid storage (separated solids) (EPA 2002b).

Manure management system data for small (fewer than 200 head) dairies were obtained at the regional level from USDA's Animal and Plant Health Inspection Service (APHIS)'s National Animal Health Monitoring System (Ott 2000). These data are based on a statistical sample of farms in the 20 U.S. states with the most dairy cows. Small operations are more likely to use liquid/slurry and solid storage management systems than anaerobic lagoon systems. The reported manure management systems were deep pit, liquid/slurry (includes slurry tank, slurry earth-basin, and aerated lagoon), anaerobic lagoon, and solid storage (includes manure pack, outside storage, and inside storage).

Data regarding the use of daily spread and pasture, range, or paddock systems for dairy cattle were obtained from personal communications with personnel from several organizations. These organizations include state NRCS offices, state extension services, state and private universities, USDA NASS, and other experts (Deal 2000, Johnson 2000, Miller 2000, Stettler 2000, Sweeten 2000, and Wright 2000). Contacts at Cornell University provided survey data on dairy manure management practices in New York (Poe et al. 1999). Census of Agriculture population data for 1992, 1997,

2002, 2007, 2012, and 2017 (USDA 2019d) were used in conjunction with the state data obtained from personal communications to determine regional percentages of total dairy cattle and dairy waste that are managed using these systems.

Of the dairies using systems other than daily spread and pasture, range, or paddock systems, some dairies reported using more than one type of manure management system. Due to limitations in how USDA APHIS collects the manure management data, the total percent of systems for a region and farm size is greater than 100 percent. However, manure is typically partitioned to use only one manure management system, rather than transferred between several different systems. Emissions estimates are only calculated for the final manure management system used for each portion of manure. To avoid double counting emissions, the reported percentages of systems in use were adjusted to equal a total of 100 percent using the same distribution of systems. For example, if USDA reported that 65 percent of dairies use deep pits to manage manure and 55 percent of dairies use anaerobic lagoons to manage manure, it was assumed that 54 percent (i.e., 65 percent divided by 120 percent) of the manure is managed with deep pits and 46 percent (i.e., 55 percent divided by 120 percent) of the manure is managed with anaerobic lagoons (ERG 2000a).

Starting in 2016, EPA estimates dairy WMS based on 2016 USDA Economic Research Service (ERS) Agricultural Resource Management Survey (ARMS) data. These data were obtained from surveys of nationally representative dairy producers. WMS data for 2016 were assumed the same for 2017 through 2022. WMS for 1997 through 2015 were interpolated between the data sources used for the 1990-1997 dairy WMS (noted above) and the 2016 ARMs data (ERG 2019).

Finally, the percentage of manure managed with anaerobic digestion (AD) systems with methane capture and combustion was added to the WMS distributions at the state-level. AD system data were obtained from EPA's AgSTAR Program's project database (EPA 2023). This database includes basic information for AD systems in the United States, based on publicly available data and data submitted by farm operators, project developers, financiers, and others involved in the development of farm AD projects.

Swine: The regional distribution of manure managed in each WMS was estimated using data from a 1995 USDA APHIS survey, EPA's Office of Water site visits, and 2009 USDA ERS ARMS data (Bush 1998, ERG 2000a, ERG 2018). The USDA APHIS data are based on a statistical sample of farms in the 16 U.S. states with the most hogs. The ERS ARMS data are based on surveys of nationally representative swine producers. Prior to 2009, operations with less than 200 head were assumed to use pasture, range, or paddock systems and swine operations with greater than 200 head were assigned WMS as obtained from USDA APHIS (Bush 1998). WMS data for 2009 were obtained from USDA ERS ARMS; WMS data for 2010 through 2022 were assumed to be the same as 2009 (ERG 2018). The percent of waste managed in each system was estimated using the EPA and USDA data broken out by geographic region and farm size. Farm-size distribution data reported in the 1992, 1997, 2002, 2007, 2012, and 2017 Census of Agriculture (USDA 2019d) were used to determine the percentage of all swine utilizing the various manure management systems. It was assumed that the swine farm size data provided for 1992 were the same as that for 1990 and 1991. Data for 1993 through 1996, 1998 through 2001, 2003 through 2006, and 2008 through 2011, and 2013 through 2016 were interpolated using the 1992, 1997, 2002, 2007, 2012, and 2017 Census data. Data for 2018 through 2022 were assumed to be the same as 2017 Census data.

Some swine operations reported using more than one management system; therefore, the total percent of systems reported by USDA for a region and farm size was greater than 100 percent. Typically, this means that a portion of the manure at a swine operation is handled in one system (e.g., liquid system), and a separate portion of the manure is handled in another system (e.g., dry system). However, it is unlikely that the same manure is moved from one system to another, which could result in increased emissions, so reported systems data were normalized to 100 percent for incorporation into the WMS distribution, using the same method as described above for dairy operations. As with dairy, AD WMS were added to the state-level WMS distribution based on data from EPA's AgSTAR database (EPA 2023).

Sheep: WMS data for sheep were obtained from USDA NASS sheep report for years 1990 through 1993 (USDA 1994). Data for 2001 are obtained from USDA APHIS's national sheep report (USDA, APHIS 2003). The USDA APHIS data are based on a statistical sample of farms in the 22 U.S. states with the most sheep. The data for years 1994-2000 are calculated assuming a linear progression from 1993 to 2001. Due to lack of additional data, data for years 2002 and beyond are assumed to be the same as 2001. Based on expert opinion (NASS staff), it was assumed that all sheep manure not deposited in feedlots was deposited on pasture, range, or paddock lands (Anderson 2000).

Goats, Horses, and Mules and Asses: WMS data for 1990 to 2022 were obtained from Appendix H of *Global Methane Emissions from Livestock and Poultry Manure* (EPA 1992). This report presents state WMS usage in percentages for the major animal types in the United States, based on information obtained from extension service personnel in each state.

It was assumed that all manure not deposited in pasture, range, or paddock lands was managed in dry systems. For mules and asses, the WMS was assumed to be the same as horses.

Poultry—Hens (one year old or older), Pullets (hens less than one year old), and Other Chickens: WMS data for 1992 were obtained from Global Methane Emissions from Livestock and Poultry Manure (EPA 1992). These data were also used to represent 1990 and 1991. The percentage of layer operations using a shallow pit flush house with anaerobic lagoon or high-rise house without bedding was obtained for 1999 from a United Egg Producers voluntary survey (UEP 1999). These data were augmented for key poultry states (AL, AR, CA, FL, GA, IA, IN, MN, MO, NC, NE, OH, PA, TX, and WA) with USDA data (USDA, APHIS 2000). It was assumed that the change in system usage between 1990 and 1999 is proportionally distributed among those years of the inventory. Data collected for EPA's Office of Water, including information collected during site visits (EPA 2002b), were used to estimate the distribution of waste by management system and animal type. For 2018, WMS data were captured from a survey of NRCS regional staff. Data for 2019 through 2022 were assumed equal to 2018. WMS data for 2000 through 2017 were linearly interpolated consistent with IPCC time-series consistency techniques (ERG 2023). As with dairy and swine, using information about AD WMS from EPA's AgSTAR database (EPA 2023), AD was added to the WMS distribution for poultry operations.

Poultry—Broilers and Turkeys: The percentage of turkeys and broilers on pasture was obtained from the Office of Air and Radiation's *Global Methane Emissions from Livestock and Poultry Manure* (EPA 1992). It was assumed that one percent of poultry waste is deposited in pastures, ranges, and paddocks (EPA 1992). The remainder of waste is assumed to be deposited in operations with bedding management. For broilers, these data were applied to 1990 through 1992. For 2018, WMS data were captured from a survey of NRCS regional staff. Data for 2019 through 2022 were assumed equal to 2018. WMS data for 1993 through 2017 were linearly interpolated consistent with IPCC time-series consistency techniques (ERG 2023). As with dairy, swine, and other poultry, AD systems were used to update the WMS distributions based on information from EPA's AgSTAR database (EPA 2023).

Step 4: Emission Factor and Other Parameter Calculations

Methane conversion factors (MCFs) and N₂O emission factors (EFs) and nitrogen loss factors used in the emission calculations were determined using the methodologies presented below.

Methane Conversion Factors (MCFs)

Climate-based IPCC default MCFs (IPCC 2006; 2019) were used for all dry systems; these factors are presented in Table A-162. A U.S.-specific methodology was used to develop MCFs for all lagoon and liquid systems.

For animal waste managed in dry systems, the appropriate IPCC default MCF was applied based on annual average temperature data. The average county and state temperature data were obtained from the National Climate Data Center (NOAA 2021) and each state and year in the inventory was assigned a climate classification of cool, temperate or warm. Although there are some specific locations in the United States that may be included in the warm climate category, no aggregated state-level annual average temperatures are included in this category. In addition, some counties in a particular state may be included in the cool climate category, although the aggregated state-level annual average temperature may be included in the temperate category. Although considering the temperatures at a state level instead of a county level may be causing some specific locations to be classified into an inappropriate climate category, using the state level annual average temperature provides an estimate that is appropriate for calculating the national average.

For anaerobic lagoons and other liquid systems, a climate-based approach based on the van't Hoff-Arrhenius equation was developed to estimate MCFs that reflects the seasonal changes in temperatures, and also accounts for long-term retention time, as discussed below. This approach is consistent with the IPCC (2006) guidelines. The van't Hoff-Arrhenius equation, with a base temperature of 30°C, is shown in the following equation (Safley and Westerman 1990):

Equation A-31: VS Proportion Available to Convert to CH₄ Based on Temperature (van't Hoff-Arrhenius *f* factor)

$$f = \exp \left[\frac{E(T_2 - T_1)}{RT_1 T_2} \right]$$

where,

f = van't Hoff-Arrhenius *f* factor, the proportion of VS that are biologically available for conversion to CH₄ based on the temperature of the system

T_1	=	303.15K
T_2	=	Ambient temperature (K) for climate zone (in this case, a weighted value for each state)
E	=	Activation energy constant (15,175 cal/mol)
R	=	Ideal gas constant (1.987 cal/K mol)

For those animal populations using liquid manure management systems or manure runoff ponds (i.e., dairy cow, dairy heifer, layers, beef in feedlots, and swine), monthly average state temperatures were based on the counties where the specific animal population resides (i.e., the temperatures were weighted based on the percent of animals located in each county). County population data were calculated from state-level population data from NASS and county-state distribution data from the 1992, 1997, 2002, 2007, 2012, and 2017 Census data (USDA 2019d). County population distribution data for 1990 and 1991 were assumed to be the same as 1992; county population distribution data for 1993 through 1996 were interpolated based on 1992 and 1997 data; county population distribution data for 1998 through 2001 were interpolated based on 1997 and 2002 data; county population distribution data for 2003 through 2006 were interpolated based on 2002 and 2007 data; county population distribution data for 2008 through 2011 were interpolated based on 2007 and 2012 data; county population distribution data for 2013 through 2016 were interpolated based on 2012 and 2017 data; county population distributions for 2018 through 2022 were assumed to be the same as 2017.

Annual MCFs for liquid systems are calculated as follows for each animal type, state, and year of the inventory:

- The weighted-average temperature for a state is calculated using the county population estimates and average monthly temperature in each county. Monthly temperatures are used to calculate a monthly van't Hoff-Arrhenius f factor, using the equation presented above. A minimum temperature of 5°C is used for uncovered anaerobic lagoons and 7.5°C is used for liquid/slurry and deep pit systems due to the biological activity in the lagoon which keeps the temperature above freezing.
- Monthly production of VS added to the system is estimated based on the animal type, number of animals present, and the volatile solids excretion rate of the animals.
- For lagoon systems, the calculation of methane includes a management and design practices (MDP) factor. The MDP factor represents management and design factors which cause a system to operate at a less than optimal level. This factor, equal to 0.8, was developed based on model comparisons to empirical CH₄ measurement data from anaerobic lagoon systems in the United States (ERG 2001).
- For all systems other than anaerobic lagoons, the amount of VS available for conversion to CH₄ each month is assumed to be equal to the amount of VS produced during the month (from Step 3). For anaerobic lagoons, the amount of VS available also includes VS that may remain in the system from previous months.
- The amount of VS consumed during the month is equal to the amount available for conversion multiplied by the f factor.
- For anaerobic lagoons, the amount of VS carried over from one month to the next is equal to the amount available for conversion minus the amount consumed. Lagoons are also modeled to have a solids clean-out once per year, occurring in the month of October.
- The estimated amount of CH₄ generated during the month is equal to the monthly VS consumed multiplied by B_0 .

The annual MCF is then calculated as:

Equation A-32: MCF for Anaerobic Lagoons and Liquid Systems

$$MCF_{\text{annual}} = \frac{CH_4 \text{ generated}_{\text{annual}}}{VS_{\text{produced}}_{\text{annual}} \times B_0}$$

where,

MCF_{annual}	=	Methane conversion factor
$VS_{\text{produced}}_{\text{annual}}$	=	Volatile solids excreted annually
B_0	=	Maximum CH ₄ producing potential of the waste

In order to account for the carry-over of VS from one year to the next, it is assumed that a portion of the VS from the previous year are available in the lagoon system in the next year. For example, the VS from October, November, and

December of 2005 are available in the lagoon system starting January of 2006 in the MCF calculation for lagoons in 2006. Following this procedure, the resulting MCF for lagoons accounts for temperature variation throughout the year, residual VS in a system (carry-over), and management and design practices that may reduce the VS available for conversion to CH₄. It is assumed that liquid-slurry systems have a retention time less than 30 days, so the liquid-slurry MCF calculation doesn't reflect the VS carry-over.

The liquid system MCFs are presented in Table A-163 by state, WMS, and animal group for 2022.

Nitrous Oxide Emission Factors and Other Parameters

Direct N₂O: Direct N₂O EFs for manure management systems (kg N₂O-N/kg excreted N) were set equal to the most recent default IPCC factors (IPCC 2006), presented in Table A-164.

Indirect N₂O: Indirect N₂O EFs account for two fractions of nitrogen losses: volatilization of ammonia (NH₃) and NO_x (Frac_{gas}) and runoff/leaching (Frac_{runoff/leach}). IPCC default indirect N₂O EFs were used to estimate indirect N₂O emissions. These factors are 0.010 kg N₂O-N/kg N for volatilization and 0.0075 kg N₂O/kg N for runoff/leaching.

Country-specific estimates of N losses were developed for Frac_{gas} and Frac_{runoff/leach} for the United States. The vast majority of volatilization losses are NH₃. Although there are also some small losses of NO_x, no quantified estimates were available for use and those losses are believed to be small (about 1 percent) in comparison to the NH₃ losses. Therefore, Frac_{gas} values were based on WMS-specific volatilization values estimated from U.S. EPA's *National Emission Inventory - Ammonia Emissions from Animal Agriculture Operations* (EPA 2005). To estimate Frac_{runoff/leach}, data from EPA's Office of Water were used that estimate the amount of runoff from beef, dairy, and heifer operations in five geographic regions of the country (EPA 2002b). These estimates were used to develop U.S. runoff factors by animal type, WMS, and region. Nitrogen losses from leaching are believed to be small in comparison to the runoff losses and there are a lack of data to quantify these losses. Therefore, leaching losses were assumed to be zero and Frac_{runoff/leach} was set equal to the runoff loss factor. Nitrogen losses from volatilization and runoff/leaching are presented in Table A-165.

Step 5: CH₄ Emission Calculations

To calculate CH₄ emissions for animals other than cattle, first the amount of VS excreted in manure that is managed in each WMS was estimated:

Equation A-33: VS Excreted for Animals Other Than Cattle

$$\text{VS excreted}_{\text{State,Animal,WMS}} = \text{Population}_{\text{State,Animal}} \times \frac{\text{TAM}}{1000} \times \text{VS} \times \text{WMS} \times 365.25$$

where,

VS excreted _{State, Animal, WMS}	=	Amount of VS excreted in manure managed in each WMS for each animal type (kg/yr)
Population _{State, Animal}	=	Annual average state animal population by animal type (head)
TAM	=	Typical animal mass (kg)
VS	=	Volatile solids production rate (kg VS/1000 kg animal mass/day)
WMS	=	Distribution of manure by WMS for each animal type in a state (percent)
365.25	=	Days per year

Using the CEFM VS data for cattle, the amount of VS excreted in manure that is managed in each WMS was estimated using the following equation:

Equation A-34: VS Excreted for Cattle

$$\text{VS excreted}_{\text{State,Animal,WMS}} = \text{Population}_{\text{State,Animal}} \times \text{VS} \times \text{WMS}$$

where,

VS excreted _{State, Animal, WMS}	=	Amount of VS excreted in manure managed in each WMS for each animal type (kg/yr)
Population _{State, Animal}	=	Annual average state animal population by animal type (head)
VS	=	Volatile solids production rate (kg VS/animal/year)
WMS	=	Distribution of manure by WMS for each animal type in a state (percent)

For all animals, the estimated amount of VS excreted into a WMS was used to calculate CH₄ emissions using the following equation:

Equation A-35: CH₄ Emissions for All Animal Types

$$CH_4 = \sum_{State, Animal, WMS} (VS \text{ excreted}_{State, Animal, WMS} \times B_0 \times MCF \times 0.662)$$

where,

CH ₄	=	CH ₄ emissions (kg CH ₄ /yr)
VS excreted _{WMS, State}	=	Amount of VS excreted in manure managed in each WMS (kg/yr)
B ₀	=	Maximum CH ₄ producing capacity (m ³ CH ₄ /kg VS)
MCF _{animal, state, WMS}	=	MCF for the animal group, state and WMS (percent)
0.662	=	Density of methane at 25° C (kg CH ₄ /m ³ CH ₄)

A calculation was developed to estimate the amount of CH₄ emitted from AD systems utilizing CH₄ capture and combustion technology. First, AD systems were assumed to produce 90 percent of B₀ of the manure. This value is applied for all climate regions and AD system types. However, this is a conservative assumption as the actual amount of CH₄ produced by each AD system is very variable and will change based on operational and climate conditions and an assumption of 90 percent is likely overestimating CH₄ production from some systems and underestimating CH₄ production in other systems. The CH₄ production of AD systems is calculated using the equation below:

Equation A-36: CH₄ Production from AD Systems

$$CH_4 \text{ Production}_{AD \text{ system}} = \text{Production}_{AD \text{ system}} \times \frac{TAM}{1000} \times VS \times B_0 \times 0.662 \times 365.25 \times 0.90$$

where,

CH ₄ Production _{AD system}	=	CH ₄ production from a particular AD system, (kg/yr)
Population _{AD state}	=	Number of animals on a particular AD system
VS	=	Volatile solids production rate (kg VS/1000 kg animal mass-day)
TAM	=	Typical Animal Mass (kg/head)
B ₀	=	Maximum CH ₄ producing capacity (CH ₄ m ³ /kg VS)
0.662	=	Density of CH ₄ at 25° C (kg CH ₄ /m ³ CH ₄)
365.25	=	Days/year
0.90	=	CH ₄ production factor for AD systems

The total amount of CH₄ produced by AD is calculated only as a means to estimate the emissions from AD; i.e., only the estimated amount of CH₄ actually entering the atmosphere from AD is reported in the inventory. The emissions to the atmosphere from AD are a result of leakage from the system (e.g., from the cover, piping, tank, etc.) and incomplete combustion and are calculated using the collection efficiency (CE) and destruction efficiency (DE) of the AD system. The three primary types of AD systems in the United States are covered lagoons, complete mix and plug flow systems. The CE of covered lagoon systems was assumed to be 75 percent, and the CE of complete mix and plug flow AD systems was assumed to be 99 percent (EPA 2008). The CH₄ DE from flaring or burning in an engine was assumed to be 98 percent; therefore, the amount of CH₄ that would not be flared or combusted was assumed to be 2 percent (EPA 2008). The amount of CH₄ produced by systems with AD was calculated with the following equation:

Equation A-37: CH₄ Emissions from AD Systems

$$CH_4 \text{ Emissions}_{AD} = \sum_{State, Animal, AD \text{ Systems}} \left(\left[CH_4 \text{ Production}_{AD \text{ system}} \times CE_{AD \text{ system}} \times (1 - DE) \right] + \left[CH_4 \text{ Production}_{AD \text{ system}} \times (1 - CE_{AD \text{ system}}) \right] \right)$$

where,

CH ₄ Emissions _{AD}	=	CH ₄ emissions from AD systems, (kg/yr)
CH ₄ Production _{AD system}	=	CH ₄ production from a particular AD system, (kg/yr)
CE _{AD system}	=	Collection efficiency of the AD system, varies by AD system type
DE	=	Destruction efficiency of the AD system, 0.98 for all systems

Step 6: N₂O Emission Calculations

Total N₂O emissions from manure management systems were calculated by summing direct and indirect N₂O emissions. The first step in estimating direct and indirect N₂O emissions was calculating the amount of N excreted in manure and managed in each WMS. For calves and animals other than cattle the following equation was used:

Equation A-38: Nex for Calves and Animal Types Other Than Cattle

$$\text{N excreted}_{\text{State,Animal,WMS}} = \text{Population}_{\text{State,Animal}} \times \text{WMS} \times \frac{\text{TAM}}{1000} \times \text{Nex} \times 365.25$$

where,

N excreted _{State, Animal, WMS}	=	Amount of N excreted in manure managed in each WMS for each animal type (kg/yr)
Population _{state}	=	Annual average state animal population by animal type (head)
WMS	=	Distribution of manure by waste management system for each animal type in a state (percent)
TAM	=	Typical animal mass (kg)
Nex	=	Nitrogen excretion rate (kg N/1000 kg animal mass/day)
365.25	=	Days per year

Using the CEFM Nex data for cattle other than calves, the amount of N excreted was calculated using the following equation:

Equation A-39: Nex from Cattle Other Than Calves

$$\text{N excreted}_{\text{State,Animal,WMS}} = \text{Population}_{\text{State,Animal}} \times \text{WMS} \times \text{Nex}$$

where,

N excreted _{State, Animal, WMS}	=	Amount of N excreted in manure managed in each WMS for each animal type (kg/yr)
Population _{state}	=	Annual average state animal population by animal type (head)
WMS	=	Distribution of manure by waste management system for each animal type in a state (percent)
Nex	=	Nitrogen excretion rate (kg N/animal/year)

For all animals, direct N₂O emissions were calculated as follows:

Equation A-40: Direct N₂O emissions from All Animal Types

$$\text{Direct N}_2\text{O} = \sum_{\text{State,Animal,WMS}} \left(\text{N excreted}_{\text{State,Animal,WMS}} \times \text{EF}_{\text{WMS}} \times \frac{44}{28} \right)$$

where,

Direct N ₂ O	=	Direct N ₂ O emissions (kg N ₂ O/yr)
N excreted _{State, Animal, WMS}	=	Amount of N excreted in manure managed in each WMS for each animal type (kg/yr)
EF _{WMS}	=	Direct N ₂ O emission factor from IPCC guidelines (kg N ₂ O-N /kg N)
44/28	=	Conversion factor of N ₂ O-N to N ₂ O

Indirect N₂O emissions were calculated for all animals with the following equation:

Equation A-41: Indirect N₂O Emissions from All Animal Types

$$\text{Indirect N}_2\text{O} = \sum_{\text{State, Animal, WMS}} \left(\left[\begin{aligned} & \text{N excreted}_{\text{State, Animal, WMS}} \times \frac{\text{Frac}_{\text{gas, WMS}}}{100} \\ & \times \text{EF}_{\text{volatilization}} \times \frac{44}{28} \end{aligned} \right] + \left[\begin{aligned} & \text{N excreted}_{\text{State, Animal, WMS}} \times \frac{\text{Frac}_{\text{runoff/leach, WMS}}}{100} \\ & \times \text{EF}_{\text{runoff/leach}} \times \frac{44}{28} \end{aligned} \right] \right)$$

where,

Indirect N ₂ O	=	Indirect N ₂ O emissions (kg N ₂ O/yr)
N excreted _{State, Animal, WMS}	=	Amount of N excreted in manure managed in each WMS for each animal type (kg/yr)
Frac _{gas, WMS}	=	Nitrogen lost through volatilization in each WMS
Frac _{runoff/leach, WMS}	=	Nitrogen lost through runoff and leaching in each WMS (data were not available for leaching so the value reflects only runoff)
EF _{volatilization}	=	Emission factor for volatilization (0.010 kg N ₂ O-N/kg N)
EF _{runoff/leach}	=	Emission factor for runoff/leaching (0.0075 kg N ₂ O-N/kg N)
44/28	=	Conversion factor of N ₂ O-N to N ₂ O

Emission estimates of CH₄ and N₂O by animal type are presented for all years of the inventory in Table A-166 and Table A-168 respectively. Emission estimates for 2022 are presented by animal type and state in Table A-170 and Table A-172 respectively.

Table A-156: Waste Characteristics Data

Animal Group	Typical Animal Mass, TAM		Total Nitrogen Excreted, Nex ^a		Maximum Methane Generation Potential, B ₀		Volatile Solids Excreted, VS ^a	
	Value (kg)	Source	Value	Source	Value (m ³ CH ₄ /kg VS added)	Source	Value	Source
Dairy Cows	680	CEFM	Table A-158	CEFM	0.24	Morris 1976	Table A-158	CEFM
Dairy Heifers	406-408	CEFM	Table A-158	CEFM	0.17	Bryant et al. 1976	Table A-158	CEFM
Feedlot Steers	419-457	CEFM	Table A-158	CEFM	0.33	Hashimoto 1981	Table A-158	CEFM
Feedlot Heifers	384-430	CEFM	Table A-158	CEFM	0.33	Hashimoto 1981	Table A-158	CEFM
NOF Bulls	831-917	CEFM	Table A-158	CEFM	0.17	Hashimoto 1981	Table A-158	CEFM
NOF Calves	122-123	CEFM	Table A-158	USDA 1996, 2008	0.17	Hashimoto 1981	Table A-158	USDA 1996, 2008
NOF Heifers	296-407	CEFM	Table A-158	CEFM	0.17	Hashimoto 1981	Table A-158	CEFM
NOF Steers	314-335	CEFM	Table A-158	CEFM	0.17	Hashimoto 1981	Table A-158	CEFM
NOF Cows	554-611	CEFM	Table A-158	CEFM	0.17	Hashimoto 1981	Table A-158	CEFM
American Bison	578.5	Meagher 1986	Table A-158	CEFM	0.17	Hashimoto 1981	Table A-158	CEFM
Market Swine <50 lbs.	13	ERG 2010a	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Market Swine <60 lbs.	16	Safley 2000	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Market Swine 50-119 lbs.	39	ERG 2010a	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Market Swine 60-119 lbs.	41	Safley 2000	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Market Swine 120-179 lbs.	68	Safley 2000	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Market Swine >180 lbs.	91	Safley 2000	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Breeding Swine	198	Safley 2000	Table A-157	USDA 1996, 2008	0.48	Hashimoto 1984	Table A-157	USDA 1996, 2008
Feedlot Sheep	25	EPA 1992	Table A-157	ASAE 1998, USDA 2008	0.36	EPA 1992	Table A-157	ASAE 1998, USDA 2008
NOF Sheep	80	EPA 1992	Table A-157	ASAE 1998, USDA 2008	0.19	EPA 1992	Table A-157	ASAE 1998, USDA 2008
Goats	64	ASAE 1998	Table A-157	ASAE 1998, USDA 2008	0.17	EPA 1992	Table A-157	ASAE 1998, USDA 2008
Horses	450	ASAE 1998	Table A-157	2008	0.33	EPA 1992	Table A-157	2008
Mules and Asses	130	IPCC 2006	Table A-157	IPCC 2006	0.33	EPA 1992	Table A-157	IPCC 2006
Hens >= 1 yr	1.8	ASAE 1998	Table A-157	USDA 1996, 2008	0.39	Hill 1982	Table A-157	USDA 1996, 2008
Pullets	1.8	ASAE 1998	Table A-157	USDA 1996, 2008	0.39	Hill 1982	Table A-157	USDA 1996, 2008
Other Chickens	1.8	ASAE 1998	Table A-157	USDA 1996, 2008	0.39	Hill 1982	Table A-157	USDA 1996, 2008
Broilers	0.9	ASAE 1998	Table A-157	USDA 1996, 2008	0.36	Hill 1984	Table A-157	USDA 1996, 2008
Turkeys	6.8	ASAE 1998	Table A-157	USDA 1996, 2008	0.36	Hill 1984	Table A-157	USDA 1996, 2008

^a Nex and VS values vary by year; Table A-158 shows state-level values for 2020 only.

Table A-157: Estimated Volatile Solids (VS) and Total Nitrogen Excreted (Nex) Production Rates by year for Swine, Poultry, Sheep, Goats, Horses, Mules and Asses, and Cattle Calves (kg/day/1000 kg animal mass)

Animal Type	1990	2005	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
VS																	
Swine, Market <50 lbs.	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8	8.8
Swine, Market 50-119 lbs.	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4
Swine, Market 120-179 lbs.	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4
Swine, Market >180 lbs.	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4	5.4
Swine, Breeding	2.6	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7
NOF Cattle Calves	6.4	7.4	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7	7.7
Sheep	9.2	8.6	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3	8.3
Goats	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5
Hens >1yr.	10.1	10.1	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2
Pullets	10.1	10.1	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2
Chickens	10.8	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0
Broilers	15.0	16.5	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0
Turkeys	9.7	8.8	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5
Horses	10.0	7.3	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1
Mules and Asses	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2
Nex																	
Swine, Market <50 lbs.	0.60	0.84	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
Swine, Market 50-119 lbs.	0.42	0.51	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Swine, Market 120-179 lbs.	0.42	0.51	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Swine, Market >180 lbs.	0.42	0.51	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Swine, Breeding	0.24	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
NOF Cattle Calves	0.30	0.41	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Sheep	0.42	0.44	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Goats	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45

State	Volatile Solids									Nitrogen Excreted								
	Dairy Cow	Dairy Heifers	Beef NOF Cow	Beef NOF Heifers	Beef NOF Steer	Beef OF Heifers	Beef OF Steer	Beef NOF Bull	American Bison	Dairy Cow	Dairy Heifers	Beef NOF Cow	Beef NOF Heifers	Beef NOF Steer	Beef OF Heifers	Beef OF Steer	Beef NOF Bull	American Bison
Nebraska	2,957	1,255	1,589	989	927	637	622	1,643	1,643	164	69	75	48	43	59	61	85	85
Nevada	2,955	1,255	1,892	1,247	1,120	637	622	1,956	1,956	164	69	59	40	33	59	61	69	69
New Hampshire	2,737	1,255	1,674	1,095	980	637	622	1,731	1,731	154	69	74	51	42	59	61	84	84
New Jersey	2,726	1,255	1,674	1,091	980	637	621	1,731	1,731	154	69	74	50	42	59	61	84	84
New Mexico	2,956	1,255	1,892	1,239	1,120	637	622	1,956	1,956	164	69	59	40	33	59	61	69	69
New York	2,976	1,255	1,674	1,086	980	637	622	1,731	1,731	164	69	74	50	42	59	61	84	84
North Carolina	2,903	1,255	1,665	1,098	974	637	622	1,721	1,721	163	69	73	50	42	59	61	83	83
North Dakota	2,804	1,255	1,589	1,020	927	637	622	1,643	1,643	157	69	75	50	43	59	61	85	85
Ohio	2,751	1,255	1,589	1,028	927	637	622	1,643	1,643	155	69	75	51	43	59	61	85	85
Oklahoma	2,475	1,255	1,665	1,071	974	637	622	1,721	1,721	143	69	73	48	42	59	61	83	83
Oregon	2,664	1,255	1,892	1,234	1,120	637	621	1,956	1,956	151	69	59	40	33	59	60	69	69
Pennsylvania	2,689	1,255	1,674	1,087	980	637	622	1,731	1,731	152	69	74	50	42	59	61	84	84
Rhode Island	2,595	1,255	1,674	1,086	980	637	622	1,731	1,731	148	69	74	50	42	59	61	84	84
South Carolina	2,492	1,255	1,665	1,103	974	637	622	1,721	1,721	145	69	73	51	42	59	61	83	83
South Dakota	2,828	1,255	1,589	1,019	927	637	622	1,643	1,643	158	69	75	50	43	59	61	85	85
Tennessee	2,522	1,255	1,665	1,087	974	637	622	1,721	1,721	147	69	73	50	42	59	61	83	83
Texas	3,017	1,255	1,665	1,056	974	637	622	1,721	1,721	166	69	73	47	42	59	61	83	83
Utah	2,844	1,255	1,892	1,243	1,120	637	622	1,956	1,956	159	69	59	40	33	59	61	69	69
Vermont	2,718	1,255	1,674	1,076	980	637	622	1,731	1,731	153	69	74	49	42	59	61	84	84
Virginia	2,675	1,255	1,665	1,085	974	637	622	1,721	1,721	153	69	73	49	42	59	61	83	83
Washington	2,901	1,255	1,892	1,213	1,120	637	622	1,956	1,956	161	69	59	39	33	59	61	69	69
West Virginia	2,221	1,255	1,674	1,093	980	637	622	1,731	1,731	132	69	74	51	42	59	61	84	84
Wisconsin	2,974	1,255	1,589	1,026	927	637	622	1,643	1,643	164	69	75	50	43	59	61	85	85
Wyoming	3,026	1,255	1,892	1,241	1,120	637	622	1,956	1,956	167	69	59	40	33	59	61	69	69

^a Beef NOF Bull values were used for American bison Nex and VS.

Source: CEFM.

Table A-159: 2022 Manure Distribution Among Waste Management Systems by Operation for Cattle (Percent)

State	Beef Feedlot Operations								Beef Not on Feed Operations	
	Dry Lot ^b	Liquid/ Slurry ^b	Pasture, Range, Paddock ^b	Solid Storage	Deep Pit	Daily Spread ^b	Composting	Cattle Deep Litter	Pasture, Range, Paddock	
Alabama	80	0	9	5	0	5	0	2	100	
Alaska	67	0	33	0	0	0	0	0	100	
Arizona	49	2	3	45	0	0	0	0	100	
Arkansas	35	0	28	13	0	18	0	6	100	
California	50	2	0	45	0	0	2	0	100	

Colorado	52	10	1	37	0	0	0	0	100
Connecticut	35	0	29	20	0	8	2	6	100
Delaware	65	0	14	8	0	9	0	4	100
Florida	100	0	0	0	0	0	0	0	100
Georgia	100	0	0	0	0	0	0	0	100
Hawaii	58	0	17	25	0	0	0	0	100
Idaho	50	0	0	50	0	0	0	0	100
Illinois	8	13	10	12	24	1	0	32	100
Indiana	34	10	6	27	4	0	1	18	100
Iowa	37	0	0	46	8	0	0	9	100
Kansas	27	8	5	32	11	0	2	16	100
Kentucky	57	0	19	13	0	9	0	3	100
Louisiana	35	0	28	13	0	19	0	6	100
Maine	93	0	3	2	0	2	0	1	100
Maryland	58	0	19	11	0	8	1	4	100
Massachusetts	46	0	5	1	0	44	2	2	100
Michigan	32	10	5	28	5	0	1	17	100
Minnesota	31	9	5	29	6	0	1	17	100
Mississippi	100	0	0	0	0	0	0	0	100
Missouri	68	0	0	16	0	0	5	10	100
Montana	48	0	4	48	0	0	0	0	100
Nebraska	45	0	2	49	1	0	0	3	100
Nevada	61	0	4	34	0	0	0	0	100
New Hampshire	35	0	28	14	0	17	0	6	100
New Jersey	20	0	55	20	0	0	0	4	100
New Mexico	50	2	3	45	0	0	0	0	100
New York	44	0	24	14	0	12	1	5	100
North Carolina	50	0	0	25	0	25	0	0	100
North Dakota	37	37	25	1	0	0	0	1	100
Ohio	2	2	0	47	2	1	0	47	100
Oklahoma	49	2	3	45	0	0	0	0	100
Oregon	50	2	0	46	0	0	2	0	100
Pennsylvania	48	0	23	12	0	11	1	5	100
Rhode Island	35	0	29	20	0	8	2	6	100
South Carolina	35	0	29	19	0	9	2	6	100
South Dakota	29	9	5	30	8	0	2	17	100
Tennessee	83	0	8	4	0	3	0	2	100
Texas	49	2	3	45	0	0	0	0	100
Utah	50	1	11	36	0	0	0	0	100
Vermont	61	0	17	9	0	9	1	4	100
Virginia	47	0	39	3	0	2	0	8	100
Washington	50	2	0	45	0	0	2	0	100

West Virginia	59	0	18	9	0	10	0	4	100
Wisconsin	37	18	1	22	3	0	1	19	100
Wyoming	50	2	5	43	0	0	0	0	100

^a In the methane inventory for manure management, the percent of dairy cows and swine with AD systems is estimated using data from EPA's AgSTAR Program.

^b Deep pit systems are their own manure management systems in the U.S. but are included under Liquid Systems in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables. For Beef Feedlots and Dairy Cows, solid storage and dry lot systems calculated separately in Table A-159, but are reported as "NE" in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables.

State	Dairy Cow Farms ^a								Dairy Heifer Facilities			
	Pasture, Range, Paddock	Daily Spread	Dry Lot	Solid Storage	Liquid/ Slurry	Anaerobic Lagoon	Deep Pit	Anaerobic Digester	Daily Spread ^b	Dry Lot ^b	Liquid/ Slurry ^b	Pasture, Range, Paddock ^b
Alabama	48	0	0	14	2	22	14	0	17	38	0	45
Alaska	25	12	0	26	5	9	22	0	6	90	1	4
Arizona	10	0	11	26	6	15	2	30	10	90	0	0
Arkansas	47	0	0	13	3	23	14	0	15	28	0	57
California	5	0	3	26	2	24	9	30	11	88	1	1
Colorado	11	0	11	41	5	30	2	0	1	98	0	1
Connecticut	15	3	0	16	6	32	26	3	43	51	0	6
Delaware	14	2	0	18	7	29	31	0	44	50	0	6
Florida	48	0	0	7	0	34	4	7	22	61	1	17
Georgia	48	0	0	9	1	36	6	0	18	42	0	40
Hawaii	4	0	4	27	2	54	9	0	0	99	1	1
Idaho	5	0	3	26	2	45	10	8	1	99	0	0
Illinois	24	0	0	23	2	33	18	1	8	87	0	5
Indiana	21	0	0	21	1	21	16	21	13	79	0	8
Iowa	20	0	0	21	2	40	16	1	10	83	0	6
Kansas	14	0	0	16	1	55	13	0	5	92	0	3
Kentucky	51	0	0	14	2	23	11	0	14	24	0	61
Louisiana	48	0	0	13	3	23	12	0	14	26	0	60
Maine	18	4	0	16	5	24	28	6	45	48	0	7
Maryland	21	4	0	16	6	23	29	0	44	49	0	7
Massachusetts	25	5	0	12	0	1	30	27	45	47	0	7
Michigan	11	3	0	22	5	34	22	4	6	91	0	3
Minnesota	16	6	0	24	5	21	23	6	10	84	0	6
Mississippi	50	0	0	14	2	16	11	6	15	28	0	57
Missouri	29	0	0	25	2	26	17	0	14	77	0	8
Montana	19	0	0	21	4	31	18	7	4	93	0	3
Nebraska	15	0	0	18	2	50	15	0	6	90	0	4
Nevada	11	0	0	14	2	61	13	0	0	99	0	0
New Hampshire	21	4	0	17	5	22	31	0	44	49	0	7

New Jersey	27	5	0	16	6	16	29	0	45	47	0	8
New Mexico	10	0	11	42	6	30	2	0	10	90	0	0
New York	14	3	0	15	0	34	25	9	45	48	0	7
North Carolina	48	0	0	10	2	31	9	0	15	31	0	54
North Dakota	18	0	0	19	3	44	16	0	11	83	0	6
Ohio	24	0	0	23	2	32	17	3	14	78	0	8
Oklahoma	11	0	8	41	5	23	12	0	6	94	0	0
Oregon	9	0	3	24	4	17	11	33	0	80	1	20
Pennsylvania	27	6	0	16	2	17	29	3	47	44	0	9
Rhode Island	29	6	0	17	5	14	30	0	47	44	0	9
South Carolina	45	0	0	10	2	33	11	0	15	31	0	54
South Dakota	14	0	0	16	2	53	14	1	8	87	0	5
Tennessee	48	0	0	12	2	26	11	0	15	26	0	59
Texas	11	0	10	41	5	18	3	12	8	92	0	0
Utah	12	0	9	40	3	28	7	1	1	98	0	1
Vermont	14	3	0	16	0	27	26	13	44	49	0	7
Virginia	49	0	0	12	1	26	11	2	15	28	0	57
Washington	8	0	3	25	3	46	10	6	0	83	1	17
West Virginia	29	6	0	17	5	13	30	0	45	48	0	7
Wisconsin	15	5	0	24	3	23	23	7	12	82	0	7
Wyoming	16	0	0	18	2	49	15	0	12	81	0	7

^a In the methane inventory for manure management, the percent of dairy cows and swine with AD systems is estimated using data from EPA's AgSTAR Program.

^b Deep pit systems are their own manure management systems in the U.S. but are included under Liquid Systems in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables. For Beef Feedlots and Dairy Cows, solid storage and dry lot systems calculated separately in Table A-159, but are reported as "NE" in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables.

Table A-160: 2022 Manure Distribution Among Waste Management Systems by Operation for Livestock Other Than Cattle (Percent)

State	Swine Operations ^a							Layer Operations							
	Pasture, Range, Paddock	Solid Storage	Liquid/ Anaerobic Slurry	Lagoon	Deep Pit	Deep Pit (<1 month)	Anaerobic Digester	Anaerobic Lagoon	Poultry without Litter	Poultry with Litter	Pasture, Range, Paddock	Liquid/ Slurry	Composting	Solid Storage	Anaerobic Digester
Alabama	15	0	29	30	12	14	0	0	8	50	0	8	0	33	0
Alaska	57	0	3	2	34	4	0	0	0	96	2	0	0	2	0
Arizona	19	0	28	29	11	13	0	0	15	34	2	1	6	42	0
Arkansas	6	0	60	24	5	2	3	0	0	75	0	0	0	25	0
California	15	0	28	29	13	14	0	0	0	68	11	0	11	10	0
Colorado	2	0	52	0	23	22	1	0	0	52	0	0	7	41	0
Connecticut	66	0	2	2	26	4	0	1	21	29	2	10	7	31	0
Delaware	29	0	4	5	56	5	0	0	50	0	0	0	0	50	0

Florida	53	0	20	14	9	5	0	0	25	25	0	25	0	25	0
Georgia	13	0	56	27	3	1	0	0	8	50	0	8	0	33	0
Hawaii	42	0	22	18	11	7	0	0	0	68	11	0	11	10	0
Idaho	16	0	16	3	57	8	0	0	0	46	8	0	15	31	0
Illinois	2	0	15	7	71	5	0	0	50	0	0	0	5	45	0
Indiana	1	0	3	12	78	7	0	0	42	8	4	0	1	45	0
Iowa	1	0	10	4	80	5	0	0	45	2	5	0	0	48	0
Kansas	1	0	13	35	21	30	0	0	42	8	4	0	1	45	0
Kentucky	8	0	19	21	31	21	0	1	18	29	2	10	7	31	3
Louisiana	67	0	17	9	6	2	0	0	0	50	0	0	0	50	0
Maine	74	0	2	1	20	4	0	1	21	29	2	10	7	31	0
Maryland	37	0	10	2	44	6	0	1	17	29	2	10	7	31	4
Massachusetts	60	0	2	2	31	4	0	0	4	44	8	0	21	21	0
Michigan	3	0	12	6	69	9	0	0	42	8	4	0	1	45	0
Minnesota	1	0	3	2	88	5	0	0	42	8	4	0	1	45	0
Mississippi	2	0	31	32	13	18	4	0	8	50	0	8	0	33	0
Missouri	2	0	16	24	34	15	10	1	13	45	10	1	0	31	0
Montana	3	0	21	2	64	9	0	0	10	40	0	3	0	47	0
Nebraska	2	0	9	22	49	19	0	0	48	0	5	0	0	48	0
Nevada	12	0	29	32	12	15	0	0	15	34	2	1	6	42	0
New Hampshire	65	0	2	2	27	4	0	1	21	29	2	10	7	31	0
New Jersey	54	0	3	3	36	4	0	0	50	0	0	50	0	0	0
New Mexico	67	0	17	9	6	2	0	0	15	34	2	1	6	42	0
New York	41	0	6	3	44	5	0	1	21	29	2	10	7	31	0
North Carolina	1	0	33	46	1	16	2	3	0	50	0	0	0	48	0
North Dakota	2	0	21	2	65	9	0	0	42	8	4	0	1	45	0
Ohio	1	0	10	9	67	13	0	0	45	1	2	0	0	49	3
Oklahoma	1	0	11	53	2	32	1	0	15	34	2	1	6	42	0
Oregon	51	0	20	15	9	5	0	0	0	40	20	0	22	18	0
Pennsylvania	1	0	8	4	76	9	2	1	21	29	2	10	7	31	0
Rhode Island	64	0	2	2	28	4	0	1	21	29	2	10	7	31	0
South Carolina	6	0	30	28	13	16	6	0	4	50	0	8	0	33	4
South Dakota	1	0	17	11	57	14	0	0	42	8	4	0	1	45	0
Tennessee	7	0	30	33	13	16	0	1	21	29	2	10	7	31	0
Texas	6	0	31	20	13	17	14	0	15	34	2	1	6	42	0
Utah	1	0	22	2	36	9	30	0	50	0	0	0	0	50	0
Vermont	69	0	2	1	24	4	0	1	21	29	2	10	7	31	0
Virginia	6	0	14	29	15	35	0	0	0	50	0	0	15	35	0
Washington	35	0	12	2	45	7	0	0	0	68	11	0	11	10	0
West Virginia	82	0	1	0	13	3	0	1	21	29	2	10	7	31	0
Wisconsin	15	0	23	1	57	4	0	0	50	0	0	0	0	50	0

Wyoming	3	0	21	2	59	9	5	0	15	34	2	1	6	42	0
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^a In the methane inventory for manure management, the percent of dairy cows and swine with AD systems is estimated using data from EPA's AgSTAR Program.

Deep pit systems are their own manure management systems in the U.S. but are included under Liquid Systems in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables.

Source(s): See *Step 3: Waste Management System Usage Data*.

State	Broiler Operations						Turkey Operations		Sheep	
	Pasture, Range, Paddock	Poultry with Litter	Poultry without Litter	Composting	Solid Storage	Anaerobic Digester	Pasture, Range, Paddock	Poultry with Litter	Dry Lot	Pasture, Range, Paddock
Alabama	0	58	0	1	41	0	1	99	95	5
Alaska	5	0	90	0	5	0	1	99	31	69
Arizona	3	49	0	7	42	0	1	99	28	72
Arkansas	0	75	0	0	25	0	1	99	83	18
California	3	25	45	0	27	0	1	99	31	69
Colorado	0	50	0	5	45	0	1	99	28	72
Connecticut	4	59	2	3	32	0	1	99	95	5
Delaware	0	50	0	0	50	0	1	99	95	5
Florida	0	50	0	0	50	0	1	99	95	5
Georgia	0	58	0	1	41	0	1	99	95	5
Hawaii	3	25	45	0	27	0	1	99	31	69
Idaho	8	46	0	15	31	0	1	99	28	72
Illinois	0	50	0	0	50	0	1	99	83	18
Indiana	2	56	0	0	42	0	1	99	83	18
Iowa	0	50	0	0	50	0	1	99	83	18
Kansas	2	56	0	0	42	0	1	99	83	18
Kentucky	4	59	2	3	32	0	1	99	95	5
Louisiana	0	50	0	3	48	0	1	99	83	18
Maine	4	59	2	3	32	0	1	99	95	5
Maryland	4	59	2	3	32	0	1	99	95	5
Massachusetts	15	46	9	3	27	0	1	99	95	5
Michigan	2	56	0	0	42	0	1	99	83	18
Minnesota	2	56	0	0	42	0	1	99	83	18
Mississippi	0	58	0	1	41	0	1	99	95	5
Missouri	8	39	0	0	52	0	1	99	83	18
Montana	0	50	0	0	50	0	1	99	28	72
Nebraska	1	50	1	0	47	0	1	99	83	18
Nevada	3	49	0	7	42	0	1	99	28	72
New Hampshire	4	59	2	3	32	0	1	99	95	5
New Jersey	0	100	0	0	0	0	1	99	95	5
New Mexico	3	49	0	7	42	0	1	99	28	72

New York	4	59	2	3	32	0	1	99	95	5
North Carolina	0	50	0	0	50	0	1	99	95	5
North Dakota	2	56	0	0	42	0	1	99	83	18
Ohio	2	96	0	0	2	0	1	99	95	5
Oklahoma	3	49	0	7	42	0	1	99	83	18
Oregon	0	50	0	0	50	0	1	99	31	69
Pennsylvania	4	59	2	3	32	0	1	99	95	5
Rhode Island	4	59	2	3	32	0	1	99	95	5
South Carolina	0	58	0	1	41	0	1	99	95	5
South Dakota	2	56	0	0	42	0	1	99	83	18
Tennessee	4	59	2	3	32	0	1	99	95	5
Texas	3	49	0	7	42	0	1	99	28	72
Utah	3	49	0	7	42	0	1	99	28	72
Vermont	4	59	2	3	32	0	1	99	95	5
Virginia	5	48	0	14	33	0	1	99	95	5
Washington	3	25	45	0	27	0	1	99	31	69
West Virginia	4	59	2	3	32	0	1	99	95	5
Wisconsin	0	50	0	0	50	0	1	99	83	18
Wyoming	3	49	0	7	42	0	1	99	28	72

^a In the methane inventory for manure management, the percent of dairy cows and swine with AD systems is estimated using data from EPA's AgSTAR Program.

Deep pit systems are their own manure management systems in the U.S. but are included under Liquid Systems in the UNFCCC CRTs due to lack of a separate allocation for those systems within the tables.

^b Because manure from beef feedlots and dairy heifers may be managed for long periods of time in multiple systems (i.e., both drylot and runoff collection pond), the percent of manure that generates emissions is greater than 100 percent.

Source(s): See *Step 3: Waste Management System Usage Data*.

Table A-161: Manure Management System Descriptions

Manure Management System	Description
Pasture, Range, Paddock	The manure from pasture and range grazing animals is allowed to lie as is and is not managed. Methane emissions are accounted for under Manure Management, but the N ₂ O emissions from manure deposited on PRP are included under the Agricultural Soil Management category.
Daily Spread	Manure is routinely removed from a confinement facility and is applied to cropland or pasture within 24 hours of excretion. Methane and indirect N ₂ O emissions are accounted for under Manure Management. Direct N ₂ O emissions from land application are included under the Agricultural Soil Management category.
Solid Storage	The storage of manure, typically for a period of several months, in unconfined piles or stacks. Manure is able to be stacked due to the presence of a sufficient amount of bedding material or loss of moisture by evaporation.
Composting	Composting in windrows with regular (at least daily) turning for mixing and aeration, with or without runoff/leaching containment.
Dry Lot	A paved or unpaved open confinement area without any significant vegetative cover where accumulating manure may be removed periodically. Dry lots are most typically found in dry climates but also are used in humid climates.
Liquid/Slurry	Manure is stored as excreted or with some minimal addition of water to facilitate handling and is stored in either tanks or earthen ponds, usually for periods less than one year.
Anaerobic Lagoon	Uncovered anaerobic lagoons are designed and operated to combine waste stabilization and storage. Lagoon supernatant is usually used to remove manure from the associated confinement facilities to the lagoon. Anaerobic lagoons are designed with varying lengths of storage (up to a year or greater), depending on the climate region, the VS loading rate, and other operational factors. Anaerobic lagoons accumulate sludge over time, diminishing treatment capacity. Lagoons must be cleaned out once every 5 to 15 years, and the sludge is typically applied to agricultural lands. The water from the lagoon may be recycled as flush water or used to irrigate and fertilize fields. Lagoons are sometimes used in combination with a solids separator, typically for dairy waste. Solids separators help control the buildup of nondegradable material such as straw or other bedding materials.
Anaerobic Digester	Animal excreta with or without straw are collected and anaerobically digested in a large containment vessel (complete mix or plug flow digester) or covered lagoon. Digesters are designed and operated for waste stabilization by the microbial reduction of complex organic compounds to CO ₂ and CH ₄ , which is captured and flared or used as a fuel.
Deep Pit	Collection and storage of manure usually with little or no added water typically below a slatted floor in an enclosed animal confinement facility. Typical storage periods range from 5 to 12 months, after which manure is removed from the pit and transferred to a treatment system or applied to land.
Poultry with Litter	Enclosed poultry houses use bedding derived from wood shavings, rice hulls, chopped straw, peanut hulls, or other products, depending on availability. The bedding absorbs moisture and dilutes the manure produced by the birds. Litter is typically cleaned out completely once a year. These manure systems are typically used for all poultry breeder flocks and for the production of meat type chickens (broilers) and other fowl.
Poultry without Litter	In high-rise cages or scrape-out/belt systems, manure is excreted onto the floor below with no bedding to absorb moisture. The ventilation system dries the manure as it is stored. When designed and operated properly, this high-rise system is a form of passive windrow composting.

^a Manure management system descriptions and the classification of manure as managed or unmanaged are based on the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Volume 4: Agriculture, Forestry and Other Land Use, Chapter 10: Emissions from Livestock and Manure Management, Tables 10.18 and 10.21) and the Development Document for the Final Revisions to the National Pollutant Discharge Elimination System Regulation and the Effluent Guidelines for Concentrated Animal Feeding Operations (EPA-821-R-03-001, December 2002).

Table A-162: Methane Conversion Factors (Percent) for Dry Systems

Waste Management System	Cool Climate MCF	Temperate Climate MCF	Warm Climate MCF
Aerobic Treatment	0	0	0
Anaerobic Digester	0	0	0
Cattle Deep Litter (<1 month)	2.75	6.5	18
Cattle Deep Litter (>1 month)	20	39	67.5
Composting - In Vessel	0.5	0.5	0.5
Composting - Static Pile	1	2	2.5
Composting-Extensive/ Passive	1	2	2.5
Composting-Intensive	0.5	1	1.5
Daily Spread	0.1	0.5	1
Dry Lot	1	1.5	2
Fuel	10	10	10
Pasture	0.47	0.47	0.47
Poultry with bedding	1.5	1.5	1.5
Poultry without bedding	1.5	1.5	1.5
Solid Storage	2	4	5

Source: IPCC (2019).

Table A-163: Methane Conversion Factors by State for Liquid Systems for 2022 (Percent)

State	Dairy		Swine		Beef	Poultry	
	Anaerobic Lagoon	Liquid/Slurry and Deep Pit	Anaerobic Lagoon	Liquid/Slurry and Pit Storage	Liquid/Slurry and Deep Pit	Anaerobic Lagoon	Liquid/Slurry
Alabama	74	40	74	40	42	74	40
Alaska	48	15	48	15	15	48	15
Arizona	78	58	76	47	44	75	37
Arkansas	74	38	75	41	39	74	39
California	75	34	75	34	45	75	34
Colorado	67	23	70	26	25	66	22
Connecticut	71	27	71	26	27	71	27
Delaware	74	32	74	33	32	74	33
Florida	78	58	77	56	52	77	56
Georgia	75	43	75	41	48	74	40
Hawaii	77	59	77	59	59	77	59
Idaho	71	25	67	22	23	66	22
Illinois	72	30	72	29	29	72	30
Indiana	71	28	71	28	28	71	28
Iowa	70	26	70	27	27	70	27
Kansas	75	35	75	34	35	75	35
Kentucky	73	33	73	34	32	73	34
Louisiana	76	49	75	48	50	75	47
Maine	65	22	65	22	22	65	22
Maryland	73	31	73	32	31	73	31
Massachusetts	69	25	70	26	26	70	26
Michigan	68	24	68	25	25	68	24
Minnesota	68	24	69	25	25	68	24
Mississippi	75	44	75	43	46	75	44
Missouri	74	34	73	32	32	74	34

Montana	63	20	66	22	22	66	22
Nebraska	73	29	73	29	29	73	29
Nevada	72	27	72	27	25	73	30
New Hampshire	66	23	67	23	22	66	23
New Jersey	73	30	73	30	29	73	30
New Mexico	73	33	71	28	31	72	30
New York	67	23	68	24	24	67	24
North Carolina	73	34	75	39	34	73	35
North Dakota	67	23	66	22	23	67	23
Ohio	70	27	71	28	28	71	28
Oklahoma	76	43	75	39	39	75	43
Oregon	67	23	66	22	23	66	22
Pennsylvania	71	27	71	27	27	72	29
Rhode Island	71	27	71	27	27	71	27
South Carolina	75	41	75	42	39	75	41
South Dakota	70	26	70	26	26	70	26
Tennessee	73	33	74	37	34	73	35
Texas	75	43	75	46	43	76	52
Utah	67	23	66	22	24	68	23
Vermont	64	21	64	21	21	64	21
Virginia	71	29	74	34	29	72	31
Washington	67	22	67	22	24	67	23
West Virginia	70	27	70	27	26	70	26
Wisconsin	66	23	68	24	24	68	25
Wyoming	64	20	65	21	23	65	21

Note: MCFs developed using Tier 2 methods described in 2006 IPCC Guidelines, Section 10.4.2.

Table A-164: Direct Nitrous Oxide Emission Factors (kg N₂O-N/kg N excreted)

Waste Management System	Direct N ₂ O Emission Factor
Aerobic Treatment (forced aeration)	0.005
Aerobic Treatment (natural aeration)	0.01
Anaerobic Digester	0.0006
Anaerobic Lagoon	0
Cattle Deep Bedding/Litter (active mix)	0.07
Cattle Deep Bedding/Litter (no mix)	0.01
Composting_in vessel	0.006
Composting_intensive	0.005
Composting_passive	0.01
Composting_static	0.01
Daily Spread	0
Pit Storage	0.002
Dry Lot	0.02
Fuel	0
Liquid/Slurry	0.005
Pasture	0
Poultry with bedding	0.001
Poultry without bedding	0.001
Solid Storage	0.01

Source: IPCC (2006).

Table A-165: Indirect Nitrous Oxide Loss Factors (Percent)

Animal Type	Waste Management System	Volatilization Nitrogen Loss	Runoff/Leaching Nitrogen Loss ^a				
			Central	Pacific	Mid-Atlantic	Midwest	South
Beef Cattle	Daily Spread	7	0	0	0	0	0
Beef Cattle	Deep Pit	25	0	0	0	0	0
Beef Cattle	Dry Lot	23	1.1	3.9	3.6	1.9	4.3
Beef Cattle	Liquid/Slurry	26	0	0	0	0	0
Beef Cattle	Pasture	0	0	0	0	0	0
Beef Cattle	Solid Storage	45	0.02	0.02	0.02	0.02	0.02
Beef Cattle	Cattle Deep Litter (>1 month)	25	0.035	0.035	0.035	0.035	0.035
Beef Cattle	Composting_intensive	65	0.06	0.06	0.06	0.06	0.06
Dairy Cattle	Anaerobic Lagoon	43	0.2	0.8	0.7	0.4	0.9
Dairy Cattle	Daily Spread	10	0	0	0	0	0
Dairy Cattle	Deep Pit	24	0	0	0	0	0
Dairy Cattle	Dry Lot	15	0.6	2	1.8	0.9	2.2
Dairy Cattle	Liquid/Slurry	26	0.2	0.8	0.7	0.4	0.9
Dairy Cattle	Pasture	0	0	0	0	0	0
Dairy Cattle	Solid Storage	27	0.2	0	0	0	0
American Bison	Pasture	0	0	0	0	0	0
Goats	Dry Lot	23	1.1	3.9	3.6	1.9	4.3
Goats	Pasture	0	0	0	0	0	0
Horses	Dry Lot	23	0	0	0	0	0
Horses	Pasture	0	0	0	0	0	0
Mules and Asses	Dry Lot	23	0	0	0	0	0
Mules and Asses	Pasture	0	0	0	0	0	0
Poultry	Anaerobic Lagoon	54	0.2	0.8	0.7	0.4	0.9
Poultry	Liquid/Slurry	26	0.2	0.8	0.7	0.4	0.9
Poultry	Pasture	0	0	0	0	0	0
Poultry	Poultry with bedding	26	0	0	0	0	0
Poultry	Poultry without bedding	34	0	0	0	0	0
Poultry	Solid Storage	8	0	0	0	0	0
Poultry	Composting_intensive	65	0.06	0.06	0.06	0.06	0.06
Sheep	Dry Lot	23	1.1	3.9	3.6	1.9	4.3
Sheep	Pasture	0	0	0	0	0	0
Swine	Anaerobic Lagoon	58	0.2	0.8	0.7	0.4	0.9
Swine	Deep Pit	34	0	0	0	0	0
Swine	Liquid/Slurry	26	0.2	0.8	0.7	0.4	0.9
Swine	Pasture	0	0	0	0	0	0
Swine	Solid Storage	45	0	0	0	0	0

^a Data for nitrogen losses due to leaching were not available, so the values represent only nitrogen losses due to runoff.
Source: EPA (2002b, 2005).

Table A-166: Total Methane Emissions from Livestock Manure Management (kt)^a

Animal Type	1990	2005	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Dairy Cattle	572	943	1,160	1,140	1,159	1,203	1,232	1,248	1,274	1,227	1,238	1,226	1,193
<i>Dairy Cows</i>	564	935	1,150	1,130	1,150	1,193	1,223	1,238	1,264	1,218	1,229	1,217	1,184
<i>Dairy Heifer</i>	7	7	9	8	8	9	9	9	9	8	9	8	8
<i>Dairy Calves</i>	1	1	1	1	1	1	1	1	1	1	1	1	1
Swine	621	812	821	756	719	808	846	840	882	890	888	877	851
Market Swine	482	665	678	623	586	665	699	697	730	739	741	730	707
<i>Market <50 lbs.</i>	101	128	98	88	86	95	101	100	105	104	105	102	99
<i>Market 50-119 lbs.</i>	101	131	149	136	130	145	155	153	160	163	160	159	154
<i>Market 120-179 lbs.</i>	136	184	193	179	169	192	203	200	211	211	211	210	205
<i>Market >180 lbs.</i>	144	221	238	220	201	232	241	244	254	260	265	259	249
Breeding Swine	139	147	143	133	133	143	146	143	152	152	147	147	144
Beef Cattle	63	78	110	111	114	120	132	142	149	148	150	157	154
<i>Feedlot Steers</i>	14	22	44	45	49	53	60	66	69	68	69	74	73
<i>Feedlot Heifers</i>	7	13	25	25	26	28	31	34	38	37	39	41	41
<i>NOF Bulls</i>	2	2	2	2	2	2	2	2	2	2	2	2	2
<i>Beef Calves</i>	3	3	3	3	3	3	3	3	3	3	3	3	3
<i>NOF Heifers</i>	5	5	5	5	5	5	6	6	5	5	5	5	5
<i>NOF Steers</i>	5	4	4	4	4	4	4	4	4	4	4	4	4
<i>NOF Cows</i>	27	28	27	26	26	26	27	28	28	28	28	27	27
Sheep	3	2	2	2	2	2	2	2	2	2	2	2	2
Goats	+	+	+	+	+	+	+	+	+	+	+	+	+
Poultry	135	123	111	105	103	109	108	107	108	111	109	108	108
<i>Hens >1 yr.</i>	73	51	33	31	29	28	26	23	21	23	21	21	20
<i>Total Pullets</i>	25	22	24	24	24	27	26	26	28	29	28	28	29
<i>Chickens</i>	4	3	3	3	3	3	3	3	3	3	3	3	3
<i>Broilers</i>	23	39	45	42	41	46	47	48	50	50	51	50	51
<i>Turkeys</i>	10	6	6	6	6	6	6	6	6	6	6	5	5
Horses	4	5	4	4	4	4	3	3	3	3	3	3	2
Mules and Asses	+	+	+	+	+	+	+	+	+	+	+	+	+
American Bison	+	+	+	+	+	+	+	+	+	+	+	+	+

+ Does not exceed 0.5 kt.

^a Accounts for CH₄ reductions due to capture and destruction of CH₄ at facilities using anaerobic digesters.

Table A-168: Total (Direct and Indirect) Nitrous Oxide Emissions from Livestock Manure Management (kt)

Animal Type	1990	2005	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Dairy Cattle	20.9	20.8	22.0	22.0	22.1	22.7	22.9	23.1	23.4	23.4	23.5	23.7	23.4
<i>Dairy Cows</i>	13.8	12.9	13.6	13.6	13.7	14.0	14.1	14.4	14.6	14.6	14.8	15.1	15.1
<i>Dairy Heifer</i>	7.1	7.8	8.5	8.3	8.4	8.7	8.8	8.8	8.8	8.7	8.7	8.6	8.3
<i>Dairy Calves</i>	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Swine	4.1	5.5	6.0	6.0	5.8	6.2	6.3	6.6	6.7	7.0	7.0	6.8	6.7
<i>Market Swine</i>	3.1	4.7	5.2	5.2	5.0	5.4	5.6	5.7	5.8	6.1	6.2	5.9	5.9
<i>Market <50 lbs.</i>	0.6	0.9	0.8	0.7	0.7	0.8	0.8	0.8	0.8	0.9	0.9	0.8	0.8
<i>Market 50-119 lbs.</i>	0.7	0.9	1.2	1.2	1.1	1.2	1.2	1.3	1.3	1.4	1.4	1.3	1.3
<i>Market 120-179 lbs.</i>	0.9	1.3	1.5	1.5	1.5	1.6	1.6	1.7	1.7	1.8	1.8	1.7	1.7
<i>Market >180 lbs.</i>	0.9	1.5	1.8	1.8	1.7	1.8	1.9	2.0	2.0	2.1	2.2	2.1	2.0
<i>Breeding Swine</i>	1.1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.8	0.8	0.8
Beef Cattle	19.7	22.7	21.4	21.2	20.7	20.9	21.7	22.3	22.3	22.7	23.0	24.2	24.1
<i>Feedlot Steers</i>	13.3	14.7	13.9	13.9	13.8	14.0	14.6	15.0	14.7	14.9	15.1	15.8	15.7
<i>Feedlot Heifers</i>	6.4	8.0	7.5	7.3	7.0	6.9	7.1	7.3	7.6	7.8	8.0	8.4	8.4
Sheep	0.4	1.2	1.1	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Goats	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Poultry	4.9	6.8	7.6	7.5	7.7	7.8	8.2	8.4	8.7	8.8	8.7	8.7	8.6
<i>Hens >1 yr.</i>	1.2	1.4	1.7	1.8	1.9	1.9	2.0	2.1	2.2	2.2	2.2	2.2	2.1
<i>Total Pullets</i>	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5
<i>Chickens</i>	+	+	+	+	+	+	+	+	+	+	+	+	+
<i>Broilers</i>	2.2	4.2	4.7	4.6	4.7	4.8	5.0	5.1	5.3	5.4	5.4	5.4	5.4
<i>Turkeys</i>	1.2	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6
Horses	0.3	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.2
Mules and Asses	+	+	+	+	+	+	+	+	+	+	+	+	+
American Bison	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Note: American bison are maintained entirely on pasture, range, and paddock. Emissions from manure deposited on pasture are included in the agricultural soils management sector.

+ Does not exceed 0.05 kt.

NA (Not Applicable)

Table A-169: Total (Direct and Indirect) Nitrous Oxide Emissions from Livestock Manure Management (MMT CO₂ Eq.)

Animal Type	1990	2005	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Dairy Cattle	5.5	5.5	5.8	5.8	5.9	6.0	6.1	6.1	6.2	6.2	6.2	6.3	6.2
<i>Dairy Cows</i>	3.6	3.4	3.6	3.6	3.6	3.7	3.7	3.8	3.9	3.9	3.9	4.0	4.0
<i>Dairy Heifer</i>	1.9	2.1	2.2	2.2	2.2	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.2
<i>Dairy Calves</i>	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Swine	1.1	1.5	1.6	1.6	1.5	1.6	1.7	1.7	1.8	1.8	1.9	1.8	1.8
<i>Market Swine</i>	0.8	1.2	1.4	1.4	1.3	1.4	1.5	1.5	1.5	1.6	1.6	1.6	1.6
<i>Market <50 lbs.</i>	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
<i>Market 50-119 lbs.</i>	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.3
<i>Market 120-179 lbs.</i>	0.2	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5
<i>Market >180 lbs.</i>	0.3	0.4	0.5	0.5	0.4	0.5	0.5	0.5	0.5	0.6	0.6	0.5	0.5
<i>Breeding Swine</i>	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Beef Cattle	5.2	6.0	5.7	5.6	5.5	5.5	5.7	5.9	5.9	6.0	6.1	6.4	6.4
<i>Feedlot Steers</i>	3.5	3.9	3.7	3.7	3.6	3.7	3.9	4.0	3.9	3.9	4.0	4.2	4.2
<i>Feedlot Heifers</i>	1.7	2.1	2.0	1.9	1.8	1.8	1.9	1.9	2.0	2.1	2.1	2.2	2.2
Sheep	0.1	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Goats	+	+	+	+	+	+	+	+	+	+	+	+	+
Poultry	1.3	1.8	2.0	2.0	2.0	2.1	2.2	2.2	2.3	2.3	2.3	2.3	2.3
<i>Hens >1 yr.</i>	0.3	0.4	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6
<i>Total Pullets</i>	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
<i>Chickens</i>	+	+	+	+	+	+	+	+	+	+	+	+	+
<i>Broilers</i>	0.6	1.1	1.3	1.2	1.2	1.3	1.3	1.4	1.4	1.4	1.4	1.4	1.4
<i>Turkeys</i>	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Horses	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Mules and Asses	+	+	+	+	+	+	+	+	+	+	+	+	+
American Bison	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

+ Does not exceed 0.05 MMT CO₂ Eq.

NA (Not Applicable)

Note: American bison are maintained entirely on pasture, range, and paddock. Emissions from manure deposited on pasture are included in the agricultural soils management sector.

Oklahoma	0.1983	0.3691	0.0777	0.0435	0.1319	0.0650	0.0199	0.1368	0.0008	0.0170	0.0031	0.0104	0.0007	NA	1.0742
Oregon	0.0785	0.1470	0.1931	0.1025	0.0004	0.0001	0.0127	0.0116	+	0.0181	0.0017	0.0065	0.0002	NA	0.5724
Pennsylvania	0.0326	0.0607	0.5067	0.2111	0.1059	0.0177	0.1654	0.1225	0.0223	0.0366	0.0016	0.0064	0.0004	NA	1.2899
Rhode Island	+	+	0.0005	0.0005	+	+	0.0004	+	+	0.0007	+	0.0002	+	NA	0.0024
South Carolina	0.0006	0.0012	0.0067	0.0037	0.0161	0.0011	0.0255	0.1403	0.0295	0.0036	0.0013	0.0036	0.0003	NA	0.2333
South Dakota	0.2238	0.4169	0.2183	0.0814	0.1518	0.0387	0.0136	0.0001	0.0072	0.0771	0.0006	0.0041	0.0001	NA	1.2335
Tennessee	0.0111	0.0207	0.0209	0.0126	0.0240	0.0040	0.0179	0.1042	+	0.0187	0.0031	0.0087	0.0008	NA	0.2468
Texas	1.8102	3.3762	1.5085	0.5137	0.0900	0.0221	0.1664	0.4596	0.0052	0.0772	0.0236	0.0300	0.0040	NA	8.0867
Utah	0.0125	0.0233	0.2100	0.1247	0.0684	0.0086	0.0430	+	0.0135	0.0298	0.0007	0.0053	+	NA	0.5398
Vermont	0.0004	0.0008	0.1479	0.0618	0.0001	+	0.0011	0.0002	+	0.0064	0.0003	0.0006	+	NA	0.2197
Virginia	0.0071	0.0133	0.0571	0.0232	0.0263	0.0008	0.0204	0.1848	0.0443	0.0274	0.0014	0.0050	0.0003	NA	0.4115
Washington	0.1431	0.2662	0.4431	0.2530	0.0008	0.0003	0.0302	0.0138	+	0.0062	0.0009	0.0046	0.0001	NA	1.1624
West Virginia	0.0023	0.0042	0.0046	0.0023	+	+	0.0104	0.0429	0.0107	0.0122	0.0008	0.0023	0.0002	NA	0.0930
Wisconsin	0.1417	0.2646	1.8870	1.2585	0.0234	0.0060	0.0397	0.0371	0.0093	0.0269	0.0041	0.0052	0.0001	NA	3.7037
Wyoming	0.0422	0.0787	0.0123	0.0094	0.0026	0.0065	0.0002	+	+	0.0364	0.0006	0.0044	0.0001	NA	0.1934

+ Does not exceed 0.00005 kt.

NA Not Applicable

Ohio	0.0184	0.0343	0.0844	0.0583	0.0602	0.0064	0.0708	0.0113	0.0047	0.0128	0.0005	0.0024	0.0001	NA	0.3646
Oklahoma	0.0525	0.0978	0.0206	0.0115	0.0349	0.0172	0.0053	0.0363	0.0002	0.0045	0.0008	0.0028	0.0002	NA	0.2847
Oregon	0.0208	0.0390	0.0512	0.0272	0.0001	+	0.0034	0.0031	+	0.0048	0.0005	0.0017	+	NA	0.1517
Pennsylvania	0.0086	0.0161	0.1343	0.0559	0.0281	0.0047	0.0438	0.0325	0.0059	0.0097	0.0004	0.0017	0.0001	NA	0.3418
Rhode Island	+	+	0.0001	0.0001	+	+	0.0001	+	+	0.0002	+	+	+	NA	0.0006
South Carolina	0.0002	0.0003	0.0018	0.0010	0.0043	0.0003	0.0067	0.0372	0.0078	0.0009	0.0003	0.0010	0.0001	NA	0.0618
South Dakota	0.0593	0.1105	0.0578	0.0216	0.0402	0.0103	0.0036	+	0.0019	0.0204	0.0002	0.0011	+	NA	0.3269
Tennessee	0.0029	0.0055	0.0055	0.0033	0.0064	0.0011	0.0047	0.0276	+	0.0049	0.0008	0.0023	0.0002	NA	0.0654
Texas	0.4797	0.8947	0.3998	0.1361	0.0239	0.0059	0.0441	0.1218	0.0014	0.0205	0.0063	0.0079	0.0011	NA	2.1430
Utah	0.0033	0.0062	0.0556	0.0330	0.0181	0.0023	0.0114	+	0.0036	0.0079	0.0002	0.0014	+	NA	0.1431
Vermont	0.0001	0.0002	0.0392	0.0164	+	+	0.0003	+	+	0.0017	0.0001	0.0002	+	NA	0.0582
Virginia	0.0019	0.0035	0.0151	0.0062	0.0070	0.0002	0.0054	0.0490	0.0117	0.0073	0.0004	0.0013	0.0001	NA	0.1090
Washington	0.0379	0.0706	0.1174	0.0670	0.0002	0.0001	0.0080	0.0037	+	0.0016	0.0003	0.0012	+	NA	0.3080
West Virginia	0.0006	0.0011	0.0012	0.0006	+	+	0.0027	0.0114	0.0028	0.0032	0.0002	0.0006	+	NA	0.0246
Wisconsin	0.0375	0.0701	0.5001	0.3335	0.0062	0.0016	0.0105	0.0098	0.0025	0.0071	0.0011	0.0014	+	NA	0.9815
Wyoming	0.0112	0.0209	0.0032	0.0025	0.0007	0.0017	0.0001	+	+	0.0096	0.0002	0.0012	+	NA	0.0512

+ Does not exceed 0.00005 MMT CO₂ Eq.

NA Not Applicable

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3.12. Methodologies for Estimating Soil Organic C Stock Changes, Soil N₂O Emissions, and CH₄ Emissions and from Agricultural Lands (Cropland and Grassland)

This annex provides a detailed description of Tier 1, 2, and 3 methods that are used to estimate soil organic carbon stock changes for cropland remaining cropland, land converted to cropland, grassland remaining grassland and land converted to grassland; direct N₂O emissions from cropland and grassland soils; indirect N₂O emissions associated with volatilization, leaching, and runoff of nitrogen from croplands and grasslands; and CH₄ emissions from rice cultivation.

Nitrous oxide (N₂O) is produced in soils through the microbial processes of nitrification and denitrification.⁸⁵ Management influences these processes by modifying the availability of mineral nitrogen (N), which is a key control on the N₂O emissions rates (Mosier et al. 1998; Paustian et al. 2016). Emissions can occur directly in the soil where the nitrogen is made available or can be transported to another location following volatilization, leaching, or runoff, and then converted into N₂O. Management practices influence soil organic carbon stocks in agricultural soils by modifying crop and forage production and microbial decomposition (Paustian et al. 1997; Paustian et al. 2016). CH₄ emissions from rice cultivation occur under flooded conditions through the process of methanogenesis, and is influenced by water management practices, organic amendments and cultivar choice (Sanchis et al. 2014). This annex provides the underlying methodologies for these three emission sources because there is considerable overlap in the methods with most emissions estimated using the DayCent ecosystem model.

A combination of Tier 1, 2, and 3 approaches are used to estimate soil organic carbon stock changes, direct and indirect soil N₂O emissions in agricultural croplands and grasslands in agricultural croplands and grasslands, and CH₄ emissions from rice cultivation. The methodologies used to estimate soil organic carbon stock changes include:

- 1) A Tier 3 method using the DayCent ecosystem model to estimate soil organic carbon stock changes in mineral soils on non-federal lands that have less than 35 percent coarse fragments by volume and are used to produce alfalfa hay, barley, corn, cotton, dry beans, grass hay, grass-clover hay, lentils, oats, onions, peanuts, peas, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, sweet potatoes, tobacco, tomatoes, and wheat, as well as non-federal grasslands and land use change between grassland and cropland (with the crops listed above and less than 35 percent coarse fragments);
- 2) Tier 2 methods with country-specific factors for estimating mineral soil organic carbon stock changes for mineral soils that are very gravelly, cobbly, or shaley (greater than 35 percent coarse fragments by volume), are used to produce crops or have land use changes to cropland and grassland (other than the conversions between cropland and grassland that are not simulated with DayCent);
- 3) Tier 2 methods with country-specific factors for estimating mineral soil organic carbon stock changes on federal lands;
- 4) Tier 2 methods with country-specific factors for estimating losses of carbon from organic soils that are drained for agricultural production; and
- 5) Tier 2 methods for estimating additional changes in mineral soil organic carbon stocks due to additions of biosolids (i.e., treated sewage sludge) to soils.

The methodologies used to estimate soil N₂O emissions include:

- 1) A Tier 3 method using the DayCent ecosystem model to estimate direct emissions from mineral soils that have less than 35 percent coarse fragments by volume and are used to produce alfalfa hay, barley, corn, cotton, dry beans, grass hay, grass-clover hay, lentils, oats, onions, peanuts, peas, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, sweet potatoes, tobacco, tomatoes, and wheat, as well as non-federal grasslands and land

⁸⁵ Nitrification and denitrification are driven by the activity of microorganisms in soils. Nitrification is the aerobic microbial oxidation of ammonium (NH₄⁺) to nitrate (NO₃⁻), and denitrification is the anaerobic microbial reduction of nitrate to N₂. Nitrous oxide is a gaseous intermediate product in the reaction sequence of nitrification and denitrification.

use change between grassland and cropland (with the crops listed above and less than 35 percent coarse fragments);

- 2) A combination of the Tier 1 and 3 methods to estimate indirect N₂O emissions associated with management of cropland and grassland simulated with DayCent;
- 3) A Tier 1 method to estimate direct and indirect N₂O emissions from mineral soils that are not simulated with DayCent, including very gravelly, cobbly, or shaley soils (greater than 35 percent coarse fragments by volume); mineral soils with less than 35 percent coarse fragments that are used to produce crops that are not simulated by DayCent; crops that are rotated with the crops that are not simulated with DayCent; Pasture/Range/Paddock (PRP) manure nitrogen deposited on federal grasslands; and land application of biosolids (i.e., treated sewage sludge) to soils; and
- 4) A Tier 1 method to estimate direct N₂O emissions due to partial or complete drainage of organic soils in croplands and grasslands.

The methodologies used to estimate soil CH₄ emissions from rice cultivation include:

- 1) A Tier 3 method using the DayCent ecosystem model to estimate CH₄ emissions from mineral soils that have less than 35 percent coarse fragments by volume and rice grown continuously or in rotation with crops that are simulated with DayCent, including alfalfa hay, barley, corn, cotton, dry beans, grass hay, grass-clover hay, lentils, oats, onions, peanuts, peas, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, sweet potatoes, tobacco, tomatoes, and wheat; and
- 2) A Tier 1 method to estimate CH₄ emissions from all other soils used to produce rice that are not estimated with the Tier 3 method, including rice grown on organic soils (i.e., *Histosols*), mineral soils with very gravelly, cobbly, or shaley soils (greater than 35 percent coarse fragments by volume), and rice grown in rotation with crops that are not simulated by DayCent.

The Tier 3 approach is applied to most agricultural lands in the United States for estimation of soil carbon stock changes, direct soil N₂O emissions, and CH₄ emissions from rice cultivation for most agricultural lands. This approach has the following advantages over the IPCC Tier 1 and 2 approaches:

- 1) It utilizes observed weather data at sub-county scales enabling quantification of inter-annual variability in N₂O emissions and carbon stock changes, and CH₄ emissions at finer spatial scales, as opposed to a single emission factor for the entire country for soil N₂O from agricultural soils and CH₄ emissions from rice cultivation, or a broad climate region classification for soil organic carbon stock changes;
- 2) The model uses a more detailed characterization of spatially-mapped soil properties that influence soil nitrogen dynamics, as opposed to the broad soil taxonomic classifications of the IPCC methodology;
- 3) The simulation approach provides a more detailed representation of management influences and their interactions than are represented by a discrete factor-based approach in the Tier 1 and 2 methods;
- 4) The legacy effects of past management can be addressed with the Tier 3 approach such as land use change from decades prior to the inventory time period that can have ongoing effects on soil organic carbon stocks, and the ongoing effects of N fertilization that may continue to stimulate N₂O emissions in years after the application; and
- 5) Soil N₂O, CH₄ emissions and carbon stock changes are estimated on a more continuous, daily basis as a function of the interaction of climate, soil, and land management, compared with the linear rate changes that are estimated with the Tier 1 and 2 methods.

More information is provided about the model structure and evaluation of the Tier 3 method at the end of this annex (See section Tier 3 Model Description, Parameterization and Evaluation, below).

Splicing methods are used to fill gaps in the time series for the emission sources and are not described in this annex. Specifically, the splicing methods are applied when there are gaps in the activity data at the end of the time series and the Tier 1, 2 and 3 methods cannot be applied. The splicing methods are described in Box 6-6 in the Cropland Remaining Cropland section and Box 5-4 of Chapter 5.4 Agricultural Soil Management.

***Inventory* Compilation Steps**

There are five steps involved in this *Inventory* to estimate the following sources: a) soil organic carbon stock changes for cropland remaining cropland, land converted to cropland, grassland remaining grassland and land converted to grassland; b) direct N₂O emissions from croplands and grassland, c) indirect N₂O emissions from volatilization, leaching, and runoff from croplands and grasslands; and d) CH₄ emissions from rice cultivation. First, the activity data are compiled from a combination of land-use, crop, and grassland management surveys, as well as expert knowledge. In the second, third, and fourth steps, soil organic carbon stock changes, direct and indirect soil N₂O emissions, and CH₄ emissions are estimated using Tier 1, 2 and 3 methods. In the fifth step, total emissions are calculated by summing all components for soil organic carbon stock changes, N₂O emissions, and CH₄ emissions. The remainder of this annex describes the methods underlying each step.

Step 1: Derive Activity Data

This step describes how the activity data are derived to estimate soil organic carbon stock changes, direct and indirect soil N₂O emissions, and CH₄ emissions from rice cultivation. The activity data requirements include: (1) land base and history data, (2) crop-specific mineral nitrogen fertilizer rates and timing,⁸⁶ (3) crop-specific manure amendment nitrogen rates and timing, (4) other nitrogen inputs, (5) tillage practices, (6) cover crop management, (7) planting and harvesting dates for crops, (8) irrigation and water management data, (9) Enhanced Vegetation Index (EVI), (10) daily weather data, and (11) edaphic characteristics.⁸⁷

Step 1a: Activity Data for the Agricultural Land Base and Histories

The U.S. Department of Agriculture's 2017 National Resources *Inventory* (NRI) (USDA-NRCS 2020) provides the basis for identifying the U.S. agricultural land base on non-federal lands, and classifying parcels into cropland remaining cropland, land converted to cropland, grassland remaining grassland, and land converted to grassland.⁸⁸ The NRI program have data available from 1979 through 2017 (USDA-NRCS 2018a) that was extended through 2020 using the USDA-NASS Crop Data Layer (CDL) (USDA-NASS 2021, Johnson and Mueller 2010), and data provided in the National Land Cover Dataset (NLCD) (Yang et al. 2018; Fry et al. 2011; Homer et al. 2007, 2015). The time series will be further extended as new data are released by the USDA NRI program, CDL, and NLCD. USDA-NRCS does not compile data on federal lands through the NRI program so the land use data are extracted from the NLCD for NRI survey locations in federal lands.

The NRI has a stratified multi-stage sampling design, where primary sample units are stratified on the basis of county and township boundaries defined by the U.S. Public Land Survey (Nusser and Goebel 1997). Within a primary sample unit, typically a 160-acre (64.75 ha) square quarter-section, three sample locations are selected according to a restricted randomization procedure. Each sample location in the survey is assigned an area weight (expansion factor) (Nusser and Goebel 1997). The survey weight are an approximation of the amount of area with the land use and land use change history that is the same as the survey location. The NRI uses a sampling approach, and therefore there is some uncertainty associated with scaling the survey location data to a region or the country using the weights. In general, the uncertainty declines at larger scales because of a larger sample size, such as states compared to smaller county units. An extensive amount of soils, land-use, and land management data have been collected through the survey (Nusser et al. 1998). Primary sources for data include aerial photography as well as field visits and county office records.

For this *Inventory*, NRI survey data are used to inform land use and crop histories for most years between 1979 and 2017, with the exception of 1983, 1988, 1993, and 2017 to 2020. For 1983, 1988, and 1993, the time series is gap-filled using an automated set of rules so that cropping sequences are filled with the most likely crop type given the historical cropping pattern at each NRI survey location. Grassland data are reported on 5-year increments prior to 1998, but it is assumed that the land use is also grassland between the years of data collection (see Easter et al. 2008 for more information). For 2018 to 2020, the time series is extended with the crop data provided in USDA-NASS CDL and NLCD. CDL data have a 30 to 58 m spatial resolution, depending on the year, and NLCD has a 30m spatial resolution. NRI survey

⁸⁶ No data are currently available at the national scale to distinguish the type of fertilizer applied or timing of applications rates. It is a planned improvement to address variation in these practices in future inventories, such as application of enhanced efficiency fertilizers.

⁸⁷ Edaphic characteristics include such factors as soil texture and pH.

⁸⁸ Note that the *Inventory* does not currently include estimates of N₂O emissions for federal grasslands with the exception of soil N₂O from PRP manure nitrogen, i.e., manure deposited directly onto pasture, range or paddock by grazing livestock.

locations are overlaid on the CDL and NLCD in a geographic information system, and the crop types and land use are extracted to extend the crop and land use histories, in addition to the full land use histories on federal lands for the inventory analysis.

NRI survey locations are included in the land base for the agricultural emissions inventory if they are identified as cropland or grassland between 1990 and 2017 (See Section 6.1 Representation of the U.S. Land Base for more information about areas in each land use and land use change category).⁸⁹ The NRI data are harmonized with the Forest *Inventory* and Analysis Dataset, and in this process, the land use and land use change data are modified to address differences in forest land remaining forest land, land converted to forest land and forest land converted to other land uses between the two national surveys (See Section 6.1 for more information on the U.S. land representation). Through this process, an annual average of 604,090 survey locations in this NRI are designated as agricultural land on non-federal and federal lands in the conterminous United States and Hawaii.

For each year, land parcels are subdivided into cropland remaining cropland, land converted to cropland, grassland remaining grassland, and land converted to grassland. Land parcels under crop management in a specific year are classified as cropland remaining cropland if the parcel has been used as cropland for at least 20 years.⁹⁰ Similarly, land parcels under grassland management in a specific year of the inventory are classified as grassland remaining grassland if they have been designated as grassland for at least 20 years. Otherwise, land parcels are classified as land converted to cropland or land converted to grassland based on the most recent use in the inventory time period. Lands are retained in the land-use change categories (i.e., land converted to cropland and land converted to grassland) for 20 years as recommended by the IPCC (2006). Lands converted into cropland and grassland are further subdivided into the specific land use conversions (e.g., forest land converted to cropland).

The Tier 3 method using the DayCent model is applied to estimate soil organic carbon stock changes and N₂O emissions for 364,333 NRI survey locations that occur on mineral soils. Parcels of land that are not simulated with DayCent are allocated to the Tier 2 approach for estimating soil organic carbon stock change, and a Tier 1 method (IPCC 2006) to estimate soil N₂O emissions⁹¹ (Table A-174). The use of the Tier 1 and 2 methods is consistent with the IPCC (2006) decision-tree for methodological selection as more detailed or finer resolution data are not available/the DayCent model is not parameterized to utilize higher-tier methods, as described throughout this Annex 3.12. The land base for the Tier 1 and 2 methods includes an annual average of 239,757 survey locations and is comprised of (1) land parcels occurring on organic soils; (2) land parcels that include non-agricultural uses such as forest or settlements in one or more years of the inventory; (3) land parcels on mineral soils that are very gravelly, cobbly, or shaley (i.e., classified as soils that have greater than 35 percent of soil volume comprised of gravel, cobbles, or shale); or (4) land parcels that are used to produce some of the vegetable crops and perennial/horticultural crops, which are either grown continuously or in rotation with other crops.

⁸⁹ Land use for 2021 and 2022 has not been incorporated into this *Inventory* analysis, but will be updated in a future *Inventory*.

⁹⁰ NRI points are classified according to land-use history records starting in 1979 when the NRI survey began, and consequently the classifications are based on less than 20 years from 1990 to 1998.

⁹¹ The Tier 1 method for soil N₂O does not require land area data with the exception of emissions from drainage and cultivation of organic soils, so in practice the Tier 1 method is only dependent on the amount of N input to mineral soils and not the actual land area.

Table A-174: Total Cropland and Grassland Area Estimated with Tiers 1/2 and 3 *Inventory* Approaches (Million Hectares)

Year	Land Areas (million ha)				
	Mineral			Organic	
	Tier 1/2	Tier 3	Total	Tier 1/2	Total ⁹²
1990	138.78	323.28	462.06	1.41	463.47
1991	138.08	323.58	461.66	1.40	463.06
1992	137.37	323.87	461.24	1.39	462.63
1993	136.54	324.34	460.89	1.40	462.28
1994	135.76	324.76	460.52	1.39	461.91
1995	134.66	325.23	459.89	1.38	461.27
1996	133.67	325.73	459.40	1.38	460.77
1997	132.66	326.23	458.88	1.38	460.26
1998	131.79	326.71	458.50	1.37	459.87
1999	130.75	327.21	457.96	1.35	459.31
2000	130.22	327.55	457.77	1.36	459.13
2001	129.55	327.86	457.41	1.36	458.77
2002	128.88	328.17	457.04	1.36	458.40
2003	128.25	328.15	456.40	1.34	457.74
2004	127.74	328.14	455.87	1.35	457.23
2005	127.16	328.13	455.30	1.35	456.65
2006	126.60	328.16	454.76	1.35	456.11
2007	126.09	328.17	454.26	1.34	455.60
2008	125.73	328.10	453.83	1.34	455.17
2009	125.34	328.14	453.47	1.33	454.81
2010	125.03	328.04	453.06	1.33	454.40
2011	124.60	328.05	452.65	1.34	453.99
2012	124.21	328.06	452.26	1.33	453.60
2013	124.03	327.80	451.82	1.33	453.15
2014	123.76	327.54	451.30	1.32	452.62
2015	123.53	327.47	451.01	1.32	452.32
2016	122.96	327.25	450.21	1.31	451.52
2017	122.95	327.25	450.20	1.31	451.51
2018	122.91	326.76	449.67	1.30	450.96
2019	122.92	326.93	449.85	1.29	451.15
2020	123.07	325.97	449.03	1.30	450.33

Note: In the current *Inventory*, land use and management data have been incorporated through 2020. Additional data will be incorporated in the future to extend the time series of the land use data.

NRI survey locations on mineral soils are classified into specific crop categories, continuous pasture/rangeland, and other non-agricultural uses for the Tier 2 inventory analysis for soil organic carbon (Table A-175). NRI locations are assigned to IPCC input categories (low, medium, high, and high with organic amendments) according to the classification provided in IPCC (2006). For croplands on federal lands, information on specific crop systems is not available, so all croplands are assumed to be medium input. In addition, NRI differentiates between improved and unimproved grassland, where improvements include irrigation and inter-seeding of legumes. Grasslands on federal lands (as identified with the NLCD) are classified according to rangeland condition (nominal, moderately degraded and severely degraded) in areas where information is available. For lands managed for livestock grazing by the Bureau of Land Management (BLM), IPCC

⁹² The current *Inventory* includes lands from all privately-owned and federal grasslands and croplands in the conterminous United States and Hawaii, but does not include the croplands and grasslands in Alaska. This leads to a discrepancy between the total area in this table, which is included in the estimation, compared to the total managed land area in Section 6.1 Representation of the U.S. Land Base. See Planned Improvement sections in cropland remaining cropland and agricultural soil management for more information about filling these gaps in the future so that emissions and removals will be estimated for all managed land.

rangeland condition classes are interpreted at the state-level from the Rangeland *Inventory*, Monitoring and Evaluation Report (BLM 2014). In order to estimate uncertainties, NRI land-use data are based on replicate weights that allow for proper variance estimates that correctly account for the complex sampling design. In particular, the variance estimates account for spatial or temporal dependencies. For example, dependencies in land use result from the likelihood that current use is correlated with past use. These dependencies occur because as an area of a land use/management category increases, the area of another land use/management category must decline.

Table A-175: Total Land Areas by Land-Use and Management System for the Tier 2 Mineral Soil Organic Carbon Approach (Million Hectares)

Land-Use/Management System	Land Areas (million hectares)												
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Cropland Systems	24.58	24.27	23.93	23.44	22.90	22.49	22.06	21.59	20.87	20.32	19.95	19.65	19.35
Conservation Reserve Program	2.35	2.58	2.72	2.58	2.40	2.29	2.17	2.17	1.78	1.74	1.70	1.70	1.61
High Input Cropping Systems, Full Tillage	1.76	1.53	1.50	1.37	1.49	1.44	1.39	1.33	1.28	1.24	1.31	1.26	1.11
High Input Cropping Systems, Reduced Tillage	0.14	0.15	0.14	0.14	0.16	0.17	0.17	0.17	0.17	0.19	0.20	0.19	0.17
High Input Cropping Systems, No Tillage	0.06	0.08	0.08	0.09	0.09	0.10	0.12	0.11	0.12	0.13	0.15	0.15	0.14
High Input Cropping Systems with Manure, Full Tillage	0.72	0.60	0.57	0.54	0.50	0.48	0.40	0.39	0.37	0.35	0.32	0.29	0.27
High Input Cropping Systems with Manure, Reduced Tillage	0.06	0.08	0.08	0.08	0.07	0.07	0.08	0.08	0.07	0.06	0.06	0.07	0.07
High Input Cropping Systems with Manure, No Tillage	0.07	0.11	0.11	0.10	0.09	0.09	0.11	0.11	0.10	0.10	0.09	0.09	0.09
Medium Input Cropping Systems, Full Tillage	6.16	5.30	4.89	4.76	4.66	4.61	4.09	3.64	3.41	3.26	3.17	2.99	2.68
Medium Input Cropping Systems, Reduced Tillage	0.43	0.69	0.66	0.62	0.57	0.53	0.67	0.64	0.60	0.58	0.54	0.61	0.60
Medium Input Cropping Systems, No Tillage	0.38	0.70	0.67	0.63	0.59	0.56	0.79	0.76	0.71	0.66	0.64	0.75	0.74
Low Input Cropping Systems, Full Tillage	8.06	7.97	7.94	7.92	7.85	7.85	7.73	7.75	7.78	7.69	7.66	7.44	7.41
Low Input Cropping Systems, Reduced Tillage	0.13	0.19	0.19	0.18	0.18	0.17	0.24	0.22	0.22	0.19	0.20	0.22	0.22
Low Input Cropping Systems, No Tillage	0.05	0.10	0.10	0.10	0.09	0.10	0.18	0.18	0.16	0.15	0.15	0.23	0.21
Hay with Legumes or Irrigation	1.43	1.44	1.43	1.42	1.32	1.24	1.17	1.18	1.12	1.04	0.97	0.88	0.99
Hay with Legumes or Irrigation and Manure	0.43	0.41	0.44	0.48	0.45	0.43	0.43	0.44	0.45	0.43	0.40	0.39	0.48
Hay, Unimproved	0.01	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.06	0.04	0.01	0.01	0.03
Pasture with Legumes or Irrigation in Rotation	0.02	0.01	0.01	0.01	0.02	0.01	0.00	0.00	0.03	0.03	0.01	0.01	0.01

Pasture with Legumes or Irrigation and Manure, in Rotation	0.00	0.00	0.00	0.00	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Rice	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.06	0.06
Perennials	2.27	2.27	2.35	2.39	2.31	2.28	2.26	2.36	2.40	2.40	2.33	2.30	2.45
Grassland Systems	114.22	113.82	113.45	113.12	112.89	112.20	111.64	111.09	110.94	110.44	110.29	109.92	109.54
Pasture with Legumes or Irrigation	3.45	3.32	3.11	3.06	3.11	2.99	2.69	2.26	2.37	2.30	2.12	2.03	1.95
Pasture with Legumes or Irrigation and Manure	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.11	0.11	0.10	0.09	0.09
Rangelands and Unimproved Pasture	78.37	78.06	78.01	78.09	77.87	77.18	76.29	76.23	75.62	75.14	75.73	75.35	76.30
Rangelands and Unimproved Pasture, Moderately Degraded	23.60	23.75	23.85	23.72	23.75	23.88	24.31	24.20	24.97	24.96	24.30	24.44	23.43
Rangelands and Unimproved Pasture, Severely Degraded	8.66	8.56	8.35	8.12	8.02	8.01	8.22	8.27	7.87	7.93	8.04	8.02	7.78
Total	138.80	138.09	137.38	136.57	135.79	134.69	133.70	132.68	131.81	130.77	130.24	129.57	128.89

Land-Use/Management System	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Cropland Systems	19.06	18.70	18.53	18.29	18.13	17.95	17.74	17.64	17.48	17.40	17.36	17.28	17.14
Conservation Reserve Program	1.44	1.23	1.31	1.34	1.27	1.23	1.08	1.11	1.02	0.88	0.88	0.78	0.79
High Input Cropping Systems, Full Tillage	1.06	1.04	1.01	0.90	0.91	0.92	0.96	0.93	1.00	0.93	0.92	0.87	0.77
High Input Cropping Systems, Reduced Tillage	0.19	0.19	0.20	0.19	0.20	0.24	0.23	0.26	0.20	0.21	0.23	0.24	0.21
High Input Cropping Systems, No Tillage	0.15	0.16	0.16	0.14	0.13	0.13	0.14	0.15	0.15	0.14	0.15	0.15	0.14
High Input Cropping Systems with Manure, Full Tillage	0.26	0.25	0.24	0.22	0.24	0.24	0.25	0.26	0.28	0.29	0.31	0.31	0.30
High Input Cropping Systems with Manure, Reduced Tillage	0.07	0.07	0.08	0.07	0.08	0.08	0.09	0.08	0.09	0.09	0.09	0.08	0.08
High Input Cropping Systems with Manure, No Tillage	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.10	0.10	0.11	0.11	0.11	0.10
Medium Input Cropping Systems, Full Tillage	2.66	2.71	2.53	2.41	2.41	2.37	2.45	2.37	2.35	2.39	2.34	2.33	2.26
Medium Input Cropping Systems, Reduced Tillage	0.59	0.60	0.56	0.59	0.59	0.56	0.55	0.52	0.48	0.48	0.47	0.45	0.45
Medium Input Cropping Systems, No Tillage	0.71	0.69	0.65	0.65	0.66	0.65	0.65	0.62	0.64	0.65	0.65	0.64	0.63
Low Input Cropping Systems, Full Tillage	7.45	7.36	7.39	7.34	7.27	7.24	7.16	7.15	7.03	7.09	7.07	7.16	7.21
Low Input Cropping Systems, Reduced Tillage	0.21	0.19	0.19	0.23	0.20	0.19	0.18	0.18	0.21	0.19	0.16	0.16	0.16

Low Input Cropping Systems, No Tillage	0.21	0.19	0.20	0.28	0.27	0.25	0.24	0.23	0.29	0.29	0.28	0.28	0.27
Hay with Legumes or Irrigation	0.96	0.92	0.95	0.94	0.94	0.92	0.87	0.85	0.82	0.82	0.83	0.83	0.82
Hay with Legumes or Irrigation and Manure	0.44	0.42	0.39	0.40	0.38	0.34	0.32	0.33	0.30	0.30	0.31	0.29	0.28
Hay, Unimproved	0.03	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Pasture with Legumes or Irrigation in Rotation	0.02	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01
Pasture with Legumes or Irrigation and Manure, in Rotation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Rice	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.02	0.01
Perennials	2.46	2.49	2.50	2.45	2.45	2.45	2.42	2.44	2.46	2.50	2.53	2.56	2.61
Grassland Systems	109.20	109.06	108.66	108.33	107.97	107.79	107.61	107.40	107.14	106.82	106.69	106.48	106.38
Pasture with Legumes or Irrigation	1.84	1.88	1.81	1.75	1.71	1.65	1.66	1.61	1.55	1.49	1.42	1.45	1.39
Pasture with Legumes or Irrigation and Manure	0.08	0.09	0.08	0.08	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05
Rangelands and Unimproved Pasture	76.55	75.69	75.41	75.30	74.97	74.90	74.72	74.71	74.69	74.41	74.44	74.03	74.39
Rangelands and Unimproved Pasture, Moderately Degraded	22.91	22.93	22.95	22.84	22.93	22.92	22.93	22.86	22.75	22.57	22.49	22.32	22.29
Rangelands and Unimproved Pasture, Severely Degraded	7.82	8.47	8.41	8.36	8.29	8.25	8.23	8.17	8.09	8.29	8.30	8.64	8.26
Total	128.26	127.76	127.19	126.62	126.10	125.74	125.35	125.04	124.62	124.21	124.05	123.77	123.52

Land-Use/Management					
System	2016	2017	2018	2019	2020
Cropland Systems	17.05	16.92	16.86	16.77	16.69
Conservation Reserve Program	0.74	0.70	0.32	0.34	0.33
High Input Cropping Systems, Full Tillage	0.85	0.82	0.92	1.30	1.41
High Input Cropping Systems, Reduced Tillage	0.14	0.16	0.16	0.16	0.17
High Input Cropping Systems, No Tillage	0.15	0.14	0.16	0.20	0.21
High Input Cropping Systems with Manure, Full Tillage	0.31	0.30	0.30	0.28	0.27
High Input Cropping Systems with Manure, Reduced Tillage	0.07	0.07	0.08	0.08	0.07
High Input Cropping Systems with Manure, No Tillage	0.11	0.10	0.11	0.11	0.10

Medium Input Cropping Systems, Full Tillage	2.38	2.25	2.62	2.95	3.11
Medium Input Cropping Systems, Reduced Tillage	0.36	0.36	0.37	0.37	0.38
Medium Input Cropping Systems, No Tillage	0.62	0.60	0.63	0.62	0.63
Low Input Cropping Systems, Full Tillage	7.01	7.03	7.37	6.64	6.46
Low Input Cropping Systems, Reduced Tillage	0.18	0.18	0.21	0.21	0.19
Low Input Cropping Systems, No Tillage	0.38	0.38	0.40	0.37	0.34
Hay with Legumes or Irrigation	0.81	0.81	0.72	0.72	0.71
Hay with Legumes or Irrigation and Manure	0.28	0.29	0.22	0.23	0.20
Hay, Unimproved	0.02	0.03	0.01	0.00	0
Pasture with Legumes or Irrigation in Rotation	0.01	0.04	0.00	0.00	0
Pasture with Legumes or Irrigation and Manure, in Rotation	0.00	0.00	0.00	0.00	0
Rice	0.02	0.02	0.01	0.01	0.01
Perennials	2.62	2.64	2.24	2.18	2.10
Grassland Systems	105.91	106.02	106.02	106.12	106.28
Pasture with Legumes or Irrigation	1.35	1.29	1.32	1.34	1.39
Pasture with Legumes or Irrigation and Manure	0.04	0.04	0.04	0.04	0.04
Rangelands and Unimproved Pasture	74.06	73.97	74.01	74.13	74.31
Rangelands and Unimproved Pasture, Moderately Degraded	22.19	22.36	22.32	22.28	22.24
Rangelands and Unimproved Pasture, Severely Degraded	8.26	8.35	8.33	8.32	8.30
Total	122.96	122.93	122.88	122.89	122.97

Note: In the current *Inventory*, land use and management data have been incorporated through 2020. Additional data will be incorporated in the future to extend the time series of the land use data. Totals may not sum due to independent rounding.

Organic soils are categorized into land-use systems based on drainage (IPCC 2006) (Table A-176). Undrained soils are treated as having no loss of organic carbon or soil N₂O emissions. Drained soils are subdivided into those used for cultivated cropland, which are assumed to have high drainage and relatively large losses of carbon, and those used for managed pasture, which are assumed to have less drainage with smaller losses of carbon. N₂O emissions are assumed to be similar for both drained croplands and grasslands.

Table A-176: Total Land Areas for Drained Organic Soils by Land Management Category and Climate Region (Million Hectares)

IPCC Land-Use Category for Organic Soils	Land Areas (million ha)													
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Cold Temperate														
Cultivated Cropland (high drainage)	0.36	0.36	0.34	0.34	0.32	0.32	0.32	0.32	0.32	0.31	0.31	0.30	0.30	0.30

Managed Pasture (low drainage)	0.36	0.36	0.37	0.37	0.39	0.38	0.37	0.38	0.37	0.36	0.37	0.38	0.38	0.37
Undrained	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Total	0.74	0.74	0.74	0.74	0.73	0.72	0.72	0.72	0.71	0.70	0.70	0.70	0.70	0.69
Warm Temperate														
Cultivated Cropland (high drainage)	0.21	0.20	0.20	0.20	0.19	0.19	0.19	0.19	0.18	0.18	0.18	0.18	0.19	0.19
Managed Pasture (low drainage)	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07
Undrained	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Total	0.27	0.26	0.26	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.26
Tropical														
Cultivated Cropland (high drainage)	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.16	0.16	0.24	0.24	0.23
Managed Pasture (low drainage)	0.18	0.17	0.17	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.18	0.16	0.17	0.15
Undrained	0	0.00	0	0.00	0.00	0.00	0.00	0	0.00	0.07	0.08	0.00	0.00	0.00
Total	0.40	0.40	0.40	0.40	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.39

IPCC Land-Use Category for Organic Soils	Land Areas (million ha)												
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
Cold Temperature													
Cultivated Cropland (high drainage)	0.30	0.30	0.30	0.30	0.29	0.28	0.28	0.29	0.29	0.29	0.29	0.29	0.29
Managed Pasture (low drainage)	0.39	0.39	0.40	0.40	0.40	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
Undrained	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.00
Total	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.70	0.70
Warm Temperate													
Cultivated Cropland (high drainage)	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Managed Pasture (low drainage)	0.07	0.07	0.07	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06
Undrained	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Total	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.25
Tropical													
Cultivated Cropland (high drainage)	0.24	0.23	0.23	0.22	0.22	0.21	0.21	0.22	0.22	0.22	0.22	0.21	0.21
Managed Pasture (low drainage)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Undrained	0.00	0.00	0.00	0.00	0.00	0.00	0	0.00	0	0.00	0	0.00	0.00
Total	0.39	0.39	0.38	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.36	0.36

IPCC Land-Use Category for Organic Soils	Land Areas (million ha)				
	2016	2017	2018	2019	2020
Cold Temperature					
Cultivated Cropland (high drainage)	0.29	0.29	0.29	0.29	0.29
Managed Pasture (low drainage)	0.41	0.41	0.40	0.40	0.41
Undrained	0.01	0.00	0.00	0.01	0.00
Total	0.70	0.70	0.69	0.69	0.70
Warm Temperate					
Cultivated Cropland (high drainage)	0.19	0.19	0.19	0.19	0.19

Managed Pasture (low drainage)	0.06	0.06	0.06	0.06	0.06
Undrained	0.00	0.00	0.00	0.00	0.00
Total	0.25	0.25	0.25	0.25	0.26
Tropical					
Cultivated Cropland (high drainage)	0.21	0.21	0.20	0.20	0.20
Managed Pasture (low drainage)	0.15	0.15	0.15	0.15	0.14
Undrained	0	0.00	0.00	0	0.00
Total	0.36	0.35	0.35	0.35	0.34

Note: In the current *Inventory*, land use and management data have been incorporated through 2020. Additional data will be incorporated in the future to extend the time series of the land use data.

The harvested area for rice cultivation is estimated from the NRI based on survey locations classified as flooded rice (Table A-177). Ratoon crops occur in the Southeastern United States with a second season of rice during the year, including Louisiana (LSU 2015 for years 2000 through 2020) and Texas (TAMU 2015 for years 1993 through 2020), averaging 32 percent and 48 percent of rice acres planted, respectively. Florida also has a large fraction of area with ratoon crops (45 percent), but ratoon cropping is uncommon in Arkansas occurring on a relatively small fraction of fields estimated at about 1 percent. No data are available for ratoon crops in Missouri or Mississippi, and so the amount of ratooning is assumed similar to Arkansas. Ratoon rice crops are not grown in California.

Table A-177: Total Rice Harvested Area Estimated with Tier 1 and 3 *Inventory* Approaches (Million Hectares)

Year	Land Areas (Million Hectares)		
	Tier 1	Tier 3	Total
1990	0.28	1.51	1.78
1991	0.27	1.54	1.81
1992	0.28	1.68	1.96
1993	0.27	1.57	1.85
1994	0.27	1.53	1.80
1995	0.26	1.55	1.81
1996	0.27	1.52	1.78
1997	0.26	1.47	1.73
1998	0.31	1.47	1.78
1999	0.39	1.38	1.78
2000	0.43	1.47	1.90
2001	0.31	1.35	1.65
2002	0.26	1.54	1.80
2003	0.25	1.38	1.64
2004	0.22	1.44	1.66
2005	0.22	1.60	1.82
2006	0.20	1.29	1.49
2007	0.24	1.33	1.58
2008	0.19	1.25	1.43
2009	0.25	1.53	1.78
2010	0.22	1.58	1.80
2011	0.23	1.29	1.51
2012	0.23	1.19	1.41
2013	0.23	1.33	1.56
2014	0.23	1.40	1.63
2015	0.21	1.46	1.67
2016	0.25	1.45	1.69
2017	0.18	1.20	1.38

2018	0.23	1.37	1.60
2019	0.21	1.12	1.34
2020	0.22	1.41	1.63

Step 1b: Obtain Management Activity Data to estimate Soil Organic Carbon Stock Changes, Soil N₂O Emissions and Rice Cultivation CH₄ Emissions from Mineral Soils

The USDA-NRCS Conservation Effects and Assessment Project (CEAP) provides data on a variety of cropland management activities, and is used to inform the inventory analysis about tillage practices, synthetic mineral fertilization, manure amendments, cover cropping management, as well as planting and harvest dates (USDA-NRCS 2022; USDA-NRCS 2018; USDA-NRCS 2012). CEAP data are collected at a subset of NRI survey locations, and provide management information from approximately 2003 to 2006 and 2013 to 2016. The CEAP data includes additional information from NRI locations such as time of planting and harvest; amount, type and time of fertilization; implement type and timing of soil cultivation events; and type and timing of cover crop planting and termination practices.

These data are combined with other datasets in an imputation analysis to generate a time series from 1950 to 2020. For several management practices, we use gradient boosted regression (Friedman, J.H. 2001) to predict management activity data on NRI survey locations. Gradient boosted regression is a machine learning technique that combines predictions from multiple weak prediction models and outperforms many complicated machine learning algorithms. The algorithm makes predictions at specific NRI survey locations or at state or regional levels. The final imputation product includes 6 complete imputations of the management activity data in order to capture the uncertainty. The sections below provide additional information for each of the management practices.

Planting Date: CEAP data on planting dates are used to train gradient boosted regression models and predict initial planting dates on NRI survey locations. The CEAP data were grouped by crop, year, and, in the case of small grains, winter and spring growing seasons. Then predictive mean matching (Little 1988, van Buuren 2012) is used to select the final planting date for each NRI survey location from the original dates in the CEAP survey. The predictive mean matching ensures that the final imputed planting dates were consistent with those reported by farmers.

Synthetic and Manure Nitrogen Fertilizer Applications: Data on synthetic mineral nitrogen fertilizer rates are imputed based on crop-specific fertilizer rates in the USDA-NRCS CEAP products and fertilizer trends based on USDA–Economic Research Service (ERS) data. The ERS crop management data had been collected in Cropping Practices Surveys through 1995 (USDA-ERS 1997), and are now compiled as part of Agricultural Resource Management Surveys (ARMS), which started in 1996 (USDA-ERS 2020). In these surveys, data on inorganic nitrogen fertilization rates are collected for crops in the high production states and for a subset of low production states. Additional data on fertilization practices are compiled from other surveys and datasets produced by USDA (USDA 1954, 1957, 1964, 1966; USDA-NASS 1992, 1999, 2004). These data are used to build a time series of mineral fertilizer application rates for specific crops and states from 1950 to 2020. These data are then used to inform the imputation product in combination with the USDA CEAP surveys, as described previously.

Fertilizer sales data are used to check and adjust synthetic mineral fertilizer amounts that are simulated with DayCent. The total amount of synthetic fertilizer used on-farms (cropland and grazing land application) has been estimated by the USGS from 1990 through 2012 on a county scale from fertilizer sales data (Brakebill and Gronberg 2017). For 2013 through 2017, county-level fertilizer used on-farms is adjusted based on annual fluctuations in total U.S. fertilizer sales (AAPFCO 2013 through 2022).⁹³ The time series is extended through 2020 using a linear extrapolation method (IPCC 2006). The resulting data are used to check the simulated synthetic fertilizer inputs in the DayCent simulations at the state scale. Specifically, the simulated amounts of mineral fertilizer application for each state and year are compared to the sales data. If the simulated amounts exceed the sales data in a year, then the simulated N₂O emissions are reduced based on the amount of simulated fertilizer that exceeded the sales data relative to the total application of fertilizer in the DayCent simulations for the state. For example, if the simulated amount exceeded the sales data by 3 percent, then the emissions associated with synthetic mineral fertilization⁹⁴ is reduced by 3 percent (the same adjustments are also

⁹³ The fertilizer consumption data in AAPFCO are recorded in “fertilizer year” totals (i.e., July to June), but are converted to calendar year totals. This is done by assuming that approximately 35 percent of fertilizer usage occurred from July to December and 65 percent from January to June (TVA 1992b).

⁹⁴ See Step 2A for the approach that is used to disaggregate N₂O emissions from DayCent into the sources of nitrogen inputs (e.g., mineral fertilizer inputs).

made for leaching and volatilization losses of nitrogen that are used to estimate indirect N₂O emissions). This method ensures that the simulated amount of N₂O emissions and indirect nitrogen losses from synthetic mineral fertilization using bottom-up data from the ARMS and CEAP surveys are adjusted so that they are consistent with the top-down sales data. The bottom-up data from CEAP and ARMS will be further investigated in the future to evaluate the discrepancies with the sales data, and potentially improve these datasets to attain greater consistency.

The available manure for application to soils from 1990 to 2020 is estimated using methods described in the manure management section (Section 5.2) and annex (Annex 3.11), along with other data sources to estimate manure amounts from 1950 to 1990 (Haines et al. 2018, Kellogg et al. 2000). It is assumed that all available manure is applied to soils in cropland and grazing lands. Application rates at individual NRI survey locations are imputed from 1950 to 2020 using the methods described at the beginning of the Step 1b section. Similar to synthetic mineral fertilization in DayCent, total amount of manure available for application to soils is used to check and adjust the simulated amounts of manure application to soils in the DayCent simulations. There were no cases in this *Inventory* in which the amount of manure amendments in DayCent simulations exceeded the available manure for application to soils. The resulting amounts of synthetic and manure fertilizer application data are found in Table A-178.

PRP Manure Nitrogen: Another key source of nitrogen for grasslands is PRP manure nitrogen (i.e., manure deposited by grazing livestock on pasture, range or paddock). The total amount of PRP manure nitrogen is estimated using methods described in the manure management section (Section 5.2) and annex (Annex 3.11). Nitrogen from PRP animal waste deposited on non-federal grasslands in a county is estimated by multiplying the total PRP nitrogen (based on animal type and population data in a county) by the fraction of non-federal grassland area in the county. PRP manure nitrogen input rates for the Tier 3 DayCent simulations are estimated by dividing the total PRP manure nitrogen amount by the land area associated with non-federal grasslands in the county from the NRI survey data. During the simulations, the PRP nitrogen input is subdivided equally between urine and solid manure (i.e., 50:50 split), and carbon is also added with the solids using C:N ratios estimated from livestock-specific data on manure chemical content in the Agricultural Waste Management Field Handbook (USDA-NRCS 1996). Total PRP manure nitrogen added to soils is found in Table A-178.

Residue Nitrogen Inputs: Crop residue nitrogen, fixation by legumes, and nitrogen residue inputs from senesced grass litter are included as sources of nitrogen to the soil, and these sources of nitrogen are estimated in the DayCent simulations as a function of vegetation type, weather, and soil properties. That is, the model accounts for the contribution of nitrogen from crop residues to the soil profile based on simulating the growth of the crop and senescence. This includes the total nitrogen inputs of above- and below-ground nitrogen and fixed nitrogen in residues that are not harvested or burned (DayCent simulations assume that 3 percent of non-harvested above ground residues for crops are burned),⁹⁵ and the resulting amounts can be found in Table A-178.

Other Nitrogen Inputs: Other nitrogen inputs are estimated within the DayCent simulation, and thus input data are not required, including mineralization from decomposition of soil organic matter and asymbiotic fixation of nitrogen from the atmosphere. Mineralization of soil organic matter will also include the effect of land use change on this process as recommended by the IPCC (2006). The influence of additional inputs of nitrogen are estimated in the simulations so that there is full estimation of all emissions from managed lands, as recommended by the IPCC (2006). The simulated nitrogen input from soil organic matter mineralization and asymbiotic nitrogen fixation are provided in Table A-178.

Tillage Practices: Tillage practices are grouped into three categories: full, reduced, and no-tillage. Full tillage is defined as multiple tillage operations every year, including significant soil inversion (e.g., plowing, deep disking) and low surface residue coverage. This definition corresponds to the intensive tillage and “reduced” tillage systems as defined by CTIC (2004). No-till is defined as not disturbing the soil except through the use of fertilizer and seed drills and where no-till is applied to all crops in the rotation. The remainder of the cultivated area is classified as reduced tillage, including mulch tillage and ridge tillage as defined by CTIC and intermittent no-till. The specific tillage implements and applications used for different crops, rotations, and regions are derived from the 1995 Cropping Practices Survey by the Economic Research Service (USDA-ERS 1997).

Tillage practices are estimated for each cropping system based on data from the Conservation Technology Information Center for 1989 to 2004 (CTIC 2004); USDA-NRCS CEAP survey (USDA-NRCS 2018b) and OpTIS Data Product⁹⁶ from 2008 to 2020 (Hagen et al. 2020). The percentage of the land base managed with reduced till is assumed to decrease linearly

⁹⁵ Another improvement is to reconcile the amount of crop residues burned with the field burning of agricultural residues source category (Section 5.5).

⁹⁶ OpTIS data on tillage practices provided by Regrow Agriculture, Inc.

from the late 1980s to 1975, and from late 1980s to 1980 for no-till. While CEAP and OptIS programs are providing data at the field scale, CTIC compiles data on cropland area under tillage management classes by major crop species and year at the county scale. The CTIC survey involves aggregate area, and therefore they do not fully characterize tillage practices as they are applied within a management sequence (e.g., crop rotation). This is particularly true for area estimates of cropland under no-till. These estimates include a relatively high proportion of “intermittent” no-till, where no-till in one year may be followed by tillage in a subsequent year, leading to no-till practices that are not continuous in time. Estimates of the area under continuous no-till for CTIC have been provided by experts at CTIC to account for intermittent tillage activity and its impact on soil organic carbon (Towery 2001).

Tillage data are further processed to impute a tillage management system for each NRI survey location over the time series from 1975 to 2020. First, the trend in the percentages for each tillage system is modeled for each CEAP region, state and crop group using CEAP, CTIC, and OptIS data products. With the modeled target percentages, we impute a tillage management system for every NRI survey location in the “base block” of 2016-2020 for each CEAP region, state and crop group by random sampling with restrictions of the modeled predictions. Once the base block is imputed, tillage systems for remaining five-year time blocks are imputed backward in time using trending information described above. The trending information from one-time block to the next is reflected in the imputations by first constructing the 3x3 transition probability matrix, \mathbf{M} , between the two blocks. Let \mathbf{a} denote the vector of proportions in the current time block (already imputed) and let \mathbf{b} denote the vector of desired proportions in the target time block (to be imputed) based on the trending information. The rows of \mathbf{M} correspond to the tillage type (no-till, reduced till, or conventional till) in the target time block and the columns of \mathbf{M} correspond to the tillage type in the current time block. The elements of \mathbf{M} are constrained so that (a) each column is a probability distribution (all elements between 0 and 1 and column sums to 1); (b) $\mathbf{M}\mathbf{a}=\mathbf{b}$; and (c) the diagonal elements of \mathbf{M} are as large as possible. The last constraint implies as much temporal continuity as possible at a location, subject to overall trends. The solution for \mathbf{M} is obtained by a mathematical optimization technique known as linear programming. Once \mathbf{M} is obtained, it is used for imputing the tillage system as follows: determine the column that corresponds to the tillage system (imputed or real) of the current block, and use the probabilities in that column to randomly select the tillage system for the target block. Repeat the construction of \mathbf{M} and the imputation block by block backward in time to 1975. All cropland is assumed to be managed with full till prior to 1975.

Cover Crops: Cover crop data from 2000 to 2020 are based on USDA CEAP data (USDA-NRCS 2018, 2022), USDA Census of Agriculture (USDA-NASS 2012, 2017) and the OptIS data product⁹⁷ (Hagen et al. 2020). Cover crops percentages are modeled by state and crop from 2000 to 2020. NRI locations are assigned cover crop management based on random selection of locations for the base year 2020 constrained by the predicted percentages. For years before 2020 to 2000, a similar technique as in the tillage system imputation is implemented to maintain the trending and temporal continuity in assignment of cover crop management to individual NRI locations subject to overall trends.

The management activity datasets do not provide information on cover crop management prior to 2000. To address this gap, it is assumed that cover crop management was minimal prior to 1990 and the percentage of locations with cover crop management increased linearly over the decade to the levels estimated from the cover crop management data in 2000.

Irrigation: NRI (USDA-NRCS 2020) provides irrigation data starting in 1979 and differentiates between irrigated and non-irrigated land, but does not provide more detailed information on the type and intensity of irrigation. Hence, irrigation is modeled by assuming that water is applied to the level of field capacity on the day after the soil drains to 60 percent of field capacity in the DayCent model simulation. To the extend the time series to 1950, the amount of NRI survey locations with irrigation are scaled backward in time from 1979 to 1950 using historical data on irrigation management (Haines et al. 2018).

Daily Weather Data: Daily maximum/minimum temperature and precipitation data are based on gridded weather data from the PRISM Climate Group (2022). Computer-generated weather data are used to drive the DayCent model simulations because weather station data do not exist near all NRI points. The PRISM product uses interpolation algorithms to derive weather patterns for areas between the existing network of weather stations (Daly et al. 1998). PRISM weather data are available for the United States starting in the year 1981 at a 4 km resolution. Each NRI survey location is assigned the PRISM weather data for the grid cell containing the survey location.

⁹⁷ OptIS data on cover crop management provided by Regrow Agriculture, Inc.

Enhanced Vegetation Index: The Enhanced Vegetation Index (EVI) from the MODIS vegetation products, (MOD13Q1 and MYD13Q1) is an input to DayCent for estimating net primary production using the NASA-CASA production algorithm (Potter et al. 1993, 2007). MODIS imagery is collected on a nominal 8 day-time frequency when combining the two products. A best approximation of the daily time series of EVI data is derived using a smoothing process based on the Savitzky-Golay Filter (Savitzky and Golay 1964) after pre-screening for outliers and for cloud-free, high quality data as identified in the MODIS data product quality layer. The NASA-CASA production algorithm is only used for the following crops, including corn, soybeans, sorghum, cotton, wheat, and other close-grown crops such as barley and oats.⁹⁸

The MODIS EVI products have a 250 m spatial resolution, and some pixels in images have mixed land uses and crop types at this resolution, which is problematic for estimating NPP associated with a specific crop at an NRI survey location. Therefore, a threshold of 90 percent purity in an individual pixel is the cutoff for estimating NPP using the EVI data derived from the imagery (i.e., pixels with less than 90 percent purity for a crop are assumed to generate bias in the resulting NPP estimates). The USDA-NASS Crop Data Layer (CDL) (Johnson and Mueller 2010) is used to determine the purity levels of the EVI data. CDL data have a 30 to 58 m spatial resolution, depending on the year. The level of purity for individual pixels in the MODIS EVI products is determined by aggregating the crop cover data in CDL to the 250 m resolution of the EVI data. In this step, the percent cover of individual crops is determined for the 250 m EVI pixels. Pixels that do not meet a 90 percent purity level for any crop are eliminated from the dataset. The nearest pixel with at least 90 percent purity for a crop is assigned to the NRI survey location based on a 10 km buffer surrounding the survey location. EVI data are not assigned to a survey location if there are no pixels with at least 90 percent purity within the 10 km buffer. In addition, CDL does not provide full coverage for crops across the conterminous United States until 2009 so it is not possible to evaluate purity for the entire cropland area prior to 2009, and therefore some NRI locations are not simulated with the NASA-CASA algorithm until 2009. In cases where EVI data are not available, production is simulated with a single value for the maximum daily NPP, which is reduced if there is water, temperature or nutrient stress affecting plant growth.

Water Management for Rice Cultivation: Rice crop production in the United States is mostly managed with continuous flooding, but does include a minor amount of land with mid-season drainage or alternate wet-dry periods (Hardke 2015; UCCE 2015; Hollier 1999; Way et al. 2014). However, continuous flooding is applied to all rice cultivation areas in the inventory because water management data are not available. Winter flooding is another key practice associated with water management in rice fields. Winter flooding occurs on 34 percent of rice fields in California (Miller et al. 2010; Fleskes et al. 2005), and approximately 21 percent of the fields in Arkansas (Wilson and Branson 2005 and 2006; Wilson and Runsick 2007 and 2008; Wilson et al. 2009 and 2010; Hardke and Wilson 2013 and 2014; Hardke 2015). No data are available on winter flooding for Texas, Louisiana, Florida, Missouri, or Mississippi. For these states, the average amount of flooding is assumed to be similar to Arkansas. In addition, the amount of winter flooding is assumed to be relatively constant over the *Inventory* time period.

Organic Amendments for Rice Cultivation: Rice straw is not typically harvested from fields in the United States. The carbon input from rice straw is simulated directly within the DayCent model for the Tier 3 method under the assumption that no straw is harvested.

Soil Properties: Soil texture and drainage capacity (i.e., hydric vs. non-hydric soil characterization) are the main soil variables used as inputs to the DayCent model. Texture is one of the main controls on soil carbon turnover and stabilization in the model, which uses particle size fractions of sand (50-2,000 μm), silt (2-50 μm), and clay (<2 μm) as inputs. Hydric condition in soils are associated with poor drainage, and hence prone to have a high-water table for part of the year in their native (pre-cultivation) condition. Non-hydric soils are moderately to well-drained.⁹⁹ Poorly drained soils can be subject to anaerobic (lack of oxygen) conditions if water inputs (precipitation and irrigation) exceed water losses from drainage and evapotranspiration. Depending on moisture conditions, hydric soils can range from fully aerobic to completely anaerobic, varying over the year. Decomposition rates are modified according to a linear function that varies from 0.3 under completely anaerobic conditions to 1.0 under fully aerobic conditions (default parameters in DayCent).¹⁰⁰ Other soil characteristics needed in the simulation, such as field capacity and wilting-point water contents, are estimated from soil texture data using a standardized hydraulic properties calculator (Saxton et al. 1986). Soil input

⁹⁸ Additional crops and grassland will be used with the NASA-CASA method in the future, as a planned improvement.

⁹⁹ Artificial drainage (e.g., ditch- or tile-drainage) is simulated as a management variable.

¹⁰⁰ Hydric soils are primarily subject to anaerobic conditions outside the plant growing season, such as late winter or early spring prior to planting. Soils that are flooded during much of the year are typically classified as organic soils (e.g., peat), which are not simulated with the DayCent model.

data are derived from Soil Survey Geographic Database (SSURGO) (Soil Survey Staff 2020). The data are based on field measurements collected as part of soil survey and mapping. Each NRI survey location is assigned the dominant soil component in the polygon containing the point from the SSURGO data product.

Step 1c: Obtain Additional Management Activity Data for the Tier 1 Method to Estimate Soil N₂O Emissions from Mineral Soils

Synthetic Nitrogen Fertilizer: A process-of-elimination approach is used to estimate synthetic nitrogen fertilizer additions to crops in the Tier 1 method. The total amount of synthetic fertilizer used on-farms has been estimated using USGS and AAPFCO datasets, as discussed in Step 1b (Brakebill and Gronberg 2017; AAPFCO 2013 through 2022). The amount of nitrogen applied to crops in the Tier 1 method (i.e., not simulated by DayCent) is assumed to be the remainder of the fertilizer that is used on farms after subtracting the amount applied to crops and non-federal grasslands simulated by DayCent. The differences are aggregated to the national level, and PDFs are derived based on uncertainties in the amount of nitrogen applied to crops and non-federal grasslands for the Tier 3 method. Total fertilizer application to crops in the Tier 1 method is found in Table A-178.

Managed Livestock Manure and Other Organic Fertilizers: Managed manure nitrogen that is not applied to crops and grassland simulated by DayCent is assumed to be applied to other crops that are included in the Tier 1 method. The total amount of manure available for application to soils has been estimated with methods described in the manure management section (Section 5.2) and annex (Annex 3.11). Managed manure nitrogen applied to croplands for the Tier 1 method is calculated using a process of elimination approach. Specifically, the amount of managed manure nitrogen that is amended to soils for the Tier 1 method is the difference between total managed manure nitrogen available for application to soils and the amount applied in the DayCent model simulations. The fate of manure available for application to soils is summarized in Table A-178.

Estimates of total national annual nitrogen additions from other commercial organic fertilizers are derived from organic fertilizer statistics (TVA 1991 through 1994; AAPFCO 1995 through 2022).¹⁰¹ Commercial organic fertilizers include dried blood, tankage, compost, and other organic materials, which are recorded in mass units of fertilizer. These data are converted to mass units of nitrogen by multiplying the consumption values by the average organic fertilizer nitrogen content of commercial organic fertilizers, which range between 2.3 to 4.2 percent across the time series (TVA 1991 through 1994; AAPFCO 1995 through 2022). There is potential for double-counting nitrogen applications to soils for dried manure and biosolids (i.e., treated sewage sludge) that are included as commercial fertilizers because these nitrogen inputs are already addressed in the manure dataset (See manure management Section 5.2 and Annex 3.11) and biosolids (See Biosolids below) that are estimated for this *Inventory*. Therefore, to avoid double-counting, the amounts of dried manure and biosolids in other commercial organic fertilizer, which are provided in the reports¹⁰² (TVA 1991 through 1994; AAPFCO 1995 through 2022), are subtracted from the total commercial organic fertilizer before estimating emissions. The PDFs are derived for the organic fertilizer applications assuming a default ± 50 percent uncertainty. Annual consumption of other organic fertilizers is presented in Table A-178.

PRP Manure Nitrogen: Soil N₂O emissions from PRP manure nitrogen deposited on federal grasslands are estimated with a Tier 1 method. PRP manure nitrogen data are derived using methods described in the manure management section (Section 5.2) and Annex 3.11. PRP nitrogen deposited on federal grasslands is calculated using a process of elimination approach. Specifically, the amount of PRP nitrogen included in the DayCent model simulations of non-federal grasslands is subtracted from total PRP nitrogen and the difference is assumed to be deposited on federal grasslands. The total PRP manure nitrogen added to soils is found in Table A-178.

Biosolids (i.e., Treated Sewage Sludge) Amendments: Biosolids are generated from the treatment of raw sewage in public or private wastewater treatment works and are typically used as a soil amendment, or are sent to waste disposal facilities, such as landfills. In this *Inventory*, all biosolids that are amended to agricultural soils are assumed to be applied

¹⁰¹ Similar to the data for synthetic fertilizers described above, the organic fertilizer consumption data are recorded in “fertilizer year” totals, (i.e., July to June), but are converted to calendar year totals. This is done by assuming that approximately 35 percent of fertilizer usage occurred from July to December and 65 percent from January to June (TVA 1992b).

¹⁰² The amount of reported dried manure and biosolids in other organic fertilizers must be converted into units of nitrogen. While the amounts of dried manure and biosolids are provided in each report (TVA 1991 through 1994; AAPFCO 1995 through 2022), the nitrogen contents of dried manure and biosolids are only provided in AAPFCO (2000). The values are 0.5 and 6.0 percent for dried manure and biosolids, respectively.

to grasslands¹⁰³. Estimates of the amounts of biosolids nitrogen applied to agricultural lands are derived from national data on biosolids generation, disposition, and nitrogen content. Total biosolids generation data for 1990 through 2004, in dry mass units, are obtained from AAPFCO (1995 through 2004). Values for 2005 through 2022 are not available so a “least squares line” statistical extrapolation using the previous 16 years of data to impute an approximate value. The total sludge generation estimates are then converted to units of nitrogen by applying an average nitrogen content (the nitrogen content of biosolids used in estimating the total nitrogen applied from biosolids is assumed to be 3.9 percent) (AAPFCO 2000), and disaggregated into use and disposal practices using historical data in EPA (1993) and NEBRA (2007). The use and disposal practices are agricultural land application, other land application, surface disposal, incineration, landfilling, ocean dumping (ended in 1992), and other disposal methods. The resulting estimates of biosolids nitrogen applied to agricultural land are used to estimate N₂O emissions from agricultural soil management; the estimates of biosolids nitrogen applied to other land and surface-disposed are used in estimating N₂O fluxes from soils in settlements remaining settlements (see section 6.9 of the Land Use, Land-Use Change, and Forestry chapter). Biosolids disposal data are provided in Table A-178.

Residue Nitrogen Inputs: Soil N₂O emissions for residue nitrogen inputs from croplands that are not simulated by DayCent are estimated with a Tier 1 method. Annual crop production statistics for all major commodity and specialty crops are taken from U.S. Department of Agriculture crop production reports (USDA-NASS 2022). Total production for each crop is converted to tons of dry matter product using the residue dry matter fractions. Dry matter yield is then converted to tons of above- and below-ground biomass nitrogen. Above-ground biomass is calculated by using linear equations to estimate above-ground biomass given dry matter crop yields, and below-ground biomass is calculated by multiplying above-ground biomass by the below-to-above-ground biomass ratio. Nitrogen inputs are estimated by multiplying above- and below-ground biomass by respective nitrogen concentrations and by the portion of cropland that is not simulated by DayCent. All ratios and equations used to calculate residue nitrogen inputs are from IPCC (2006) and Williams (2006). PDFs are derived assuming a ±50 percent uncertainty in the yield estimates (USDA-NASS does not provide uncertainty), along with uncertainties provided by the IPCC (2006) for dry matter fractions, above-ground residue, ratio of below-ground to above-ground biomass, and residue nitrogen fractions. The resulting annual residue nitrogen inputs are presented in Table A-178.

Table A-178: Sources of Soil Nitrogen (kt N)

N Source	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
1. Synthetic Fertilizer N: Cropland	9,817	10,008	10,092	9,989	11,150	10,306	10,874	10,862	10,827	10,982
2. Synthetic Fertilizer N: Grassland	6	4	10	37	18	5	7	8	66	8
3. Managed Manure N: Cropland	2,449	2,481	2,490	2,477	2,538	2,571	2,563	2,583	2,602	2,607
4. Managed Manure N: Grassland	+	+	+	+	+	+	+	+	+	+
5. Pasture, Range, & Paddock Manure N	4,084	4,091	4,251	4,341	4,414	4,515	4,482	4,380	4,337	4,275
6. N from Crop Residue Decomposition ^a	5,539	5,662	5,351	5,736	5,545	5,875	5,703	5,599	5,613	6,278
7. N from Grass Residue Decomposition ^a	10,788	10,694	10,999	11,065	10,596	11,266	11,001	11,022	10,513	11,737
8. Min. SOM / Asymbiotic N-Fixation: Cropland ^b	10,029	9,611	9,204	10,071	9,338	10,012	9,363	9,454	10,605	9,784
9. Min. SOM / Asymbiotic N-Fixation: Grassland ^b	15,122	15,638	15,422	15,443	14,852	15,309	15,555	15,930	15,953	14,959
10. Treated Sewage Sludge N: Grassland	52	56	60	63	66	69	72	76	79	81
11. Other Organic Amendments: Cropland ^c	4	8	6	5	8	10	13	14	12	11
Total	57,890	58,252	57,885	59,227	58,525	59,938	59,634	59,929	60,607	60,720

N Source	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
1. Synthetic Fertilizer N: Cropland	10,791	10,070	10,546	10,611	11,310	10,726	10,464	11,502	10,937	9,948
2. Synthetic Fertilizer N: Grassland	24	21	22	15	57	16	8	7	18	11
3. Managed Manure N: Cropland	2,640	2,627	2,661	2,670	2,593	2,626	2,704	2,726	2,701	2,678
4. Managed Manure N: Grassland	+	+	+	+	+	+	+	+	+	+
5. Pasture, Range, & Paddock Manure N	4,182	4,178	4,186	4,191	4,144	4,195	4,248	4,139	4,099	4,066
6. N from Crop Residue Decomposition ^a	6,027	5,990	5,837	6,039	5,709	5,807	5,792	5,722	5,647	5,761
7. N from Grass Residue Decomposition ^a	10,953	11,308	11,082	11,405	10,814	11,441	11,181	11,504	11,434	10,981

¹⁰³ A portion of biosolids may be applied to croplands, but there is no national dataset to disaggregate the amounts between cropland and grassland.

8. Min. SOM / Asymbiotic N-Fixation: Cropland ^b	9,795	10,478	10,174	10,215	10,791	10,480	10,207	10,703	10,575	10,952
9. Min. SOM / Asymbiotic N-Fixation: Grassland ^b	14,646	15,080	15,322	15,449	17,064	16,096	15,767	16,635	16,112	16,328
10. Treated Sewage Sludge N: Grassland	84	86	89	92	94	94	94	93	93	93
11. Other Organic Amendments: Cropland ^c	9	7	8	8	9	10	12	15	12	10
Total	59,151	59,846	59,927	60,695	62,586	61,489	60,478	63,045	61,628	60,826

N Source	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
1. Synthetic Fertilizer N: Cropland	10,793	11,264	11,909	11,911	11,714	11,494	11,395	11,510	11,305	11,249
2. Synthetic Fertilizer N: Grassland	1	10	10	5	4	7	3	1	5	7
3. Managed Manure N: Cropland	2,666	2,694	2,721	2,701	2,693	2,756	2,821	2,894	2,937	2,970
4. Managed Manure N: Grassland	+	+	+	+	+	+	+	+	+	+
5. Pasture, Range, & Paddock Manure N	4,015	3,919	3,832	3,791	3,730	3,809	3,938	4,005	4,002	4,007
6. N from Crop Residue Decomposition ^a	6,261	6,143	5,946	5,961	6,110	5,811	5,811	5,957	6,369	5,796
7. N from Grass Residue Decomposition ^a	11,309	10,918	11,370	10,668	10,737	10,330	10,669	10,963	10,510	10,757
8. Min. SOM / Asymbiotic N-Fixation: Cropland ^b	11,742	10,386	9,649	11,329	11,702	12,189	12,404	11,738	12,768	12,294
9. Min. SOM / Asymbiotic N-Fixation: Grassland ^b	16,642	14,934	14,266	16,508	16,349	16,778	16,716	16,038	16,735	16,528
10. Treated Sewage Sludge N: Grassland	93	92	92	92	91	91	91	90	90	90
11. Other Organic Amendments: Cropland ^c	10	12	13	13	11	12	20	22	16	14
Total	63,532	60,371	59,808	62,978	63,140	63,277	63,868	63,218	64,738	63,712

N Source	2020
1. Synthetic Fertilizer N: Cropland	11,209
2. Synthetic Fertilizer N: Grassland	6
3. Managed Manure N: Cropland	2,989
4. Managed Manure N: Grassland	+
5. Pasture, Range, & Paddock Manure N	3,947
6. N from Crop Residue Decomposition ^a	6,530
7. N from Grass Residue Decomposition ^a	11,149
8. Min. SOM / Asymbiotic N-Fixation: Cropland ^b	11,179
9. Min. SOM / Asymbiotic N-Fixation: Grassland ^b	14,605
10. Treated Sewage Sludge N: Grassland	89
11. Other Organic Amendments: Cropland ^c	13
Total	61,717

+ Does not exceed 0.5 kt

^a Residue nitrogen inputs include unharvested fixed nitrogen from legumes as well as crop and grass residue nitrogen.

^b Mineralization of soil organic matter and the asymbiotic fixation of nitrogen gas.

^c Includes dried blood, tankage, compost, other. Excludes dried manure and bio-solids (i.e., treated sewage sludge) used as commercial fertilizer to avoid double counting.

Note: Most activity data were not compiled for 2021 and 2022 and used in this *Inventory*, and so a data splicing method was used to estimate emissions. Additional activity data will be collected, and the Tier 1 and 3 methods will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Step 1d: Additional Management Activity Data for Tier 2 Method to estimate Soil Organic Carbon Stock Changes in Mineral Soils

Biosolids (i.e., Treated Sewage Sludge) Amendments: Biosolids are generated from the treatment of raw sewage in public or private wastewater treatment facilities and are typically used as soil amendments or are sent for waste disposal to

landfills. In this *Inventory*, all biosolids that are amended to agricultural soils are assumed to be applied to grasslands¹⁰⁴. See section on biosolids in Step 1c for more information about the methods used to derive biosolid nitrogen estimates. The total amount of biosolid nitrogen is given in Table A-178. Biosolid nitrogen is assumed to be applied at the assimilative capacity provided in Kellogg et al. (2000), which is the amount of nutrients taken up by a crop and removed at harvest representing the recommended application rate for manure amendments. Future inventories may be revised to reflect the assimilative capacity of grasslands, but there is insufficient information to approximate the capacity in this *Inventory*. Total biosolid nitrogen available for application is divided by the assimilative capacity to estimate the total land area over which biosolids have been applied. The resulting estimates are used for the estimation of soil organic carbon stock changes associated with application of biosolids.

Wetland Reserve: Wetlands enrolled in the Conservation Reserve Program have been restored in the Northern Prairie Pothole Region through the Partners for Wildlife Program funded by the U.S. Fish and Wildlife Service (USFWS 2010). The area of restored wetlands is estimated from contract agreements (Euliss and Gleason 2002). While the contracts provide reasonable estimates of the amount of land restored in the region, they do not provide the information necessary to estimate uncertainty. Consequently, a ± 50 percent range is used to construct the PDFs for the uncertainty analysis.

Step 1e: Additional Activity Data for Indirect N₂O Emissions

A portion of the nitrogen that is applied as synthetic fertilizer, livestock manure, and biosolids (i.e., treated sewage sludge) volatilizes as NH₃ and NO_x. In turn, the volatilized nitrogen is eventually returned to soils or water bodies through atmospheric deposition, thereby increasing nitrogen availability and enhancing N₂O production. Additional nitrogen is also lost from soils through leaching of mostly NO₃⁻ as water percolates through a soil profile and through runoff with overland water flow. Nitrogen losses from leaching and runoff enter groundwater and waterways, from which a portion is emitted as N₂O. Consistent with the IPCC guidelines (2006), indirect emissions are not estimated for leaching and runoff of nitrogen in semi- arid and arid regions. Semi-arid and arid regions in the United States occur in areas where the precipitation water input does not exceed 80 percent of the potential evapotranspiration (Note: Irrigated systems are always assumed to have leaching of nitrogen even in drier climates).

Using the DayCent model with the Tier 3 method and nitrogen sources contributing to indirect emissions described in IPCC (2006) guidelines, volatilization and leaching/surface run-off of nitrogen from soils is estimated in the simulations for crops and non-federal grasslands. DayCent simulates the processes leading to these losses of nitrogen based on environmental conditions (i.e., weather patterns and soil characteristics), management impacts (e.g., plowing, irrigation, harvest), and soil nitrogen availability (Del Grosso et al. 2005, 2008a; David et al. 2009). The DayCent model accounts for losses of nitrogen from all anthropogenic activity, not just the inputs of nitrogen from synthetic mineral fertilization and organic amendments¹⁰⁵, which are addressed in the Tier 1 method. In addition, DayCent is a mass balance model and ensures that all nitrogen inputs are tracked through the flows in the ecosystem with no double counting of losses. Volatilized losses of nitrogen are summed for each day in the annual cycle to provide an estimate of the amount of nitrogen subject to indirect N₂O emissions. For non-arid regions, the daily losses of nitrogen through leaching and runoff in overland flow are summed for the annual cycle to provide an estimate of the amount of nitrogen subject to indirect N₂O emissions. Uncertainty in the estimates is derived from the variability in the fertilizer and organic amendment activity data, in addition to uncertainty in the DayCent model predictions.

The activity data to estimate the indirect N₂O emissions from volatilization, runoff and leaching in the Tier 1 method are based on the synthetic fertilizer, livestock manure, residue nitrogen inputs, biosolids nitrogen, and other nitrogen inputs in the calculation of direct emissions from agricultural mineral soils. These data are provided in Table A-178. To estimate volatilized nitrogen losses, the amount of synthetic fertilizers, manure, and biosolids are multiplied by the fraction subject to gaseous losses using the respective default values of 0.1 kg N/kg N added as mineral fertilizers and 0.2 kg N/kg N added as manure (IPCC 2006). Uncertainty in the volatilized nitrogen ranges from 0.03-0.3 kg NH₃-N+NO_x-N/kg N for synthetic fertilizer and 0.05-0.5 kg NH₃-N+NO_x-N/kg N for organic amendments (IPCC 2006). To estimate leaching/runoff losses of nitrogen from land areas that are not included in the DayCent simulations, the nitrogen additions from

¹⁰⁴ Note that there are no data available on the location of biosolid amendments and so all biosolids are applied to grasslands (future *Inventories* will incorporate new information when it is available to separate amendments between croplands and grasslands).

¹⁰⁵ The amount of volatilization and leaching are reduced if the simulated amount of synthetic mineral fertilization in DayCent exceeds the amount mineral fertilizer sales. See subsection on Synthetic and Manure Nitrogen Fertilizer Applications in Step 1b for more information.

synthetic and manure, biosolids, and above- and below-ground crop residues, are multiplied by the fraction subject to leaching/runoff losses of 0.3 kg N/kg N applied, with an uncertainty from 0.1–0.8 kg NO₃-N/kg N (IPCC 2006). As noted above, leaching is assumed to be an insignificant source of indirect N₂O emissions if the amount of precipitation does not exceed 80 percent of the potential evapotranspiration (Note: Irrigated systems are always assumed to have leaching of nitrogen even in drier climates). PDFs are derived for each of the nitrogen inputs in the same manner as direct N₂O emissions, discussed in Steps 1a and 1c.

Volatilized nitrogen is summed for losses from croplands and grasslands. Similarly, the annual amounts of nitrogen lost from soil profiles through leaching and surface runoff are summed to obtain the total losses for this pathway.

Step 1f: Additional Activity Data for Estimating CH₄ Emissions from Rice Cultivation with the Tier 1 Method

For the Tier 1 method, residues amounts are needed to estimate CH₄ emissions from rice cultivation, along with the water management data, which has been described in Step 1b. The residues are assumed to be left on the field for more than 30 days prior to cultivation and flooding for the next crop, with the exception of ratoon crops, which are assumed to have residues on the field for less than 30 days prior to the second crop in the season. To estimate the amount of rice residue, crop yield data (except rice in Florida) are compiled from USDA NASS QuickStats (USDA 2015). Rice yield data are not collected by USDA for Florida, and so are derived based on NRI crop areas and average primary and ratoon rice yields from Deren (2002). Relative proportions of ratoon crops are derived from information in several publications (Schueneman 1997, 1999, 2000, 2001; Deren 2002; Kirstein 2003, 2004, 2006; Cantens 2004, 2005; Gonzalez 2007 through 2014). The yields are multiplied by residue: crop product ratios from Strehler and Stützle (1987) to estimate rice residue input amounts for the Tier 1 method.

Step 2: Estimate Soil Organic Carbon Stock Changes, Soil N₂O Emissions, and CH₄ Emissions from Rice Cultivation for Mineral Soils

In this step, soil organic carbon stock changes, direct N₂O emissions, and CH₄ emissions from rice cultivation are estimated for cropland and grasslands. The DayCent process-based model is used for the croplands and non-federal grasslands included in the Tier 3 method. A Tier 2 method is used to estimate soil organic carbon stock changes for crop types, grasslands and soil types that are not simulated by DayCent. A Tier 1 methodology is used to estimate N₂O emissions from crops that are not simulated by DayCent, PRP manure nitrogen deposition on federal grasslands, and CH₄ emissions from rice cultivation.

Step 2a: Estimate Soil Organic Carbon Stock Changes, Soil N₂O Emissions, and CH₄ emissions for Crops and Non-Federal Grassland with the Tier 3 DayCent Model

Crops that are simulated with DayCent include alfalfa hay, barley, corn, cotton, dry beans, grass hay, grass-clover hay, lentils, oats, onions, peanuts, peas, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, sweet potatoes, tobacco, tomatoes, and wheat, which combined represent approximately 85 percent of total cropland in the United States. The DayCent simulations also include the majority of non-federal grasslands in the United States.

The methodology description is divided into two sub-steps. First, the DayCent model is used to establish the initial conditions and carbon stocks for 1979, which is the first year of the NRI survey. In the second sub-step, DayCent is used to simulate changes in soil organic carbon stocks, direct soil N₂O emissions, leaching, runoff and volatilization losses of N contributing to indirect N₂O emissions, and CH₄ emissions from rice cultivation based on the land-use and management histories recorded in the NRI (USDA-NRCS 2020).

Simulate Initial Conditions (Pre-NRI Conditions): The purpose of the DayCent model initialization is to estimate the most accurate stock for the pre-NRI history, and the distribution of organic carbon among the pools represented in the model (e.g., structural and metabolic litter pools, in addition to active, slow, and passive soil organic matter pools). Each pool has a different turnover rate (representing the heterogeneous nature of soil organic matter), and the amount of carbon in each pool at any point in time influences the forward trajectory of total soil organic carbon storage and soil nitrogen dynamics that influence soil N₂O emissions. There is currently no national set of soil carbon measurements subdivided by the pools that can be used for establishing initial conditions in the model. Sensitivity analysis of the soil organic carbon algorithms showed that the rate of change of soil organic matter is relatively insensitive to the *amount* of total soil organic carbon but is highly sensitive to the relative *distribution* of carbon among different pools (Parton et al. 1987). By simulating the historical land use prior to the inventory period, initial pool distributions are estimated in an unbiased way.

The first step involves running the model to a steady-state condition (e.g., equilibrium) under native vegetation, historical climate data based on the PRISM product (PRISM Climate Group 2022), and the soil characteristics for the NRI survey locations. Native vegetation is represented at the MLRA level for pre-settlement time periods in the United States. The model simulates pre-settlement conditions until a steady-state condition is achieved.

The second step is to simulate the period of time from European settlement and expansion of agriculture to the beginning of the NRI survey, representing the influence of historic land-use change and management, particularly the conversion of native vegetation to agricultural uses. This encompasses a varying time period from land conversion (depending on historical settlement patterns) to 1979. The information on historical cropping practices used for DayCent simulations has been gathered from a variety of sources, ranging from the historical accounts of farming practices reported in the literature (e.g., Miner 1998) to national level databases (e.g., NASS 2004). A detailed description of the data sources and assumptions used in constructing the base history scenarios of agricultural practices can be found in Williams and Paustian (2005), along with the imputed data for tillage, mineral fertilization, and irrigation histories, as described in Step 2b.

NRI History Simulations: After model initialization, DayCent is used to simulate the NRI land use and management histories from 1979 through 2020. The simulations estimate the influence of soil management on soil organic carbon stocks, direct soil N₂O emissions, and losses of nitrogen from the profile through leaching/runoff and volatilization. These simulations are also used to estimate CH₄ emissions from rice cultivation. The NRI histories, supplemented with CDL and NLCD data, identify the land use and land use change histories for the NRI survey locations, as well as cropping patterns and irrigation history (see Step 1a for description of the NRI data). The input data for the model simulations also include the PRISM weather dataset and SSURGO soils data, synthetic nitrogen fertilizer rates, managed manure amendments to cropland and grassland, manure deposition on grasslands (i.e., PRP), tillage histories, cover crop usage, and EVI data (See Step 1b for description of the inputs). There are six simulations for each NRI survey location based on the imputation product in order to capture the uncertainty in the management activity data derived by combining data from the CEAP survey, ARMS, Census of Agriculture, OpTIS data product, CTIC survey and related data. See Step 1b for more information. The simulation system incorporates a dedicated MySQL database server and a parallel processing computer cluster. Input/output operations are managed by a run control system.

Evaluating uncertainty is an integral part of the analysis and includes three components: (1) uncertainty in the management activity data inputs (input uncertainty); (2) uncertainty in the model formulation and parameterization (structural uncertainty); and (3) uncertainty in the land-use and management system areas (scaling uncertainty) (Ogle et al. 2010; Del Grosso et al. 2010, Ogle et al. 2023). For the first component, the uncertainty is based on the six imputations underlying the data product combining CEAP survey, ARMS, OpTIS data product, Census of Agriculture and CTIC survey data. See Step 1b for discussion about the imputation product. The second component deals with uncertainty inherent in model formulation and parameterization. This component is the largest source of uncertainty in the Tier 3 model-based inventory analysis, accounting for more than 80 percent of the overall uncertainty in the final estimates (Ogle et al. 2010; Del Grosso et al. 2010). An empirically based procedure is applied to develop a structural uncertainty estimator from the relationship between modeled results and field measurements from agricultural experiments (Ogle et al. 2007). The inputs to the model are essentially known in the simulations for the long-term experiments, and, therefore, the analysis is designed to evaluate uncertainties associated with the model structure (i.e., model algorithms and parameterization).

The empirical relationship between field measurements and modeled emissions/stock changes are statistically analyzed using linear-mixed effect modeling techniques. The modeled emissions are treated as a fixed effect in the statistical models. The resulting relationships are used to make an adjustment to modeled values if there are biases due to significant mismatches between the modeled and measured values. Several other variables are tested in these models including soil characteristics, geographic location (i.e., state), and management practices (e.g., tillage practices, fertilizer rates, crop type, cover crop usage, irrigation). Random effects are included in all of these models to capture the dependence in time series and data collected from the same site, which are needed to estimate appropriate standard deviations for parameter coefficients. See the Tier 3 Model Description, Parameterization and Evaluation Section, below, for more information about model evaluation, including graphs illustrating the relationships between modeled and measured values.

The third element is the uncertainty associated with scaling the DayCent results for each NRI survey location to the entire land base, using the survey weights provided with the NRI dataset. The survey weights represent the number of hectares associated with the land-use and management history for a particular survey location. The scaling uncertainty is due to the complex sampling design that selects the locations for NRI, and this uncertainty is properly reflected in the

replicate weights. The empirical variance computed from the replicate weights is an estimate of the scaling uncertainty associated with the NRI sampling design.

Uncertainty in the DayCent model estimates is quantified with two variance components (Ogle et al., 2010). The first variance component quantifies the uncertainty in management activity data, model structure and parameterization. To assess this uncertainty, carbon and nitrogen dynamics at each NRI survey location are simulated six times using the imputation product and other model driver data. Uncertainty in parameterization and model algorithms are determined using a structural uncertainty estimator derived from fitting a linear mixed-effect model (Ogle et al. 2007, 2010, 2023). The data are combined in a Monte Carlo stochastic simulation with 1,000 iterations. In each iteration, there is a random selection of management activity data from the imputation product and a random draw of parameter values for the uncertainty estimator (Ogle et al. 2010). Note that parameter values for the statistical equations (i.e., fixed effects) are selected from their joint probability distribution, along with random error associated with the time series and data collected from the same site, and the residual/unexplained error. The randomly selected parameter values and associated management information are then used as input into the linear mixed-effect model, and adjusted values are computed for each emissions/stock change estimate that was produced by DayCent. The results are used to compute the first variance component (V_1) according to the following equation:

$$V_1 = \frac{\sum_{i=1}^m \left(\theta_i - m^{-1} \sum_{i=1}^m \theta_i \right)^2}{m-1}$$

where m is the number of Monte Carlo iterations (i.e., 1000), and θ is the emissions/stock change estimate for each iteration i .

The second variance component quantifies uncertainty in scaling from the NRI survey to the entire land base and is computed with the NRI replicate weights. Specifically, the second variance component (V_2) is estimated using the following formula:

$$V_2 = \left(\frac{28}{29} \right) \sum_{l=1}^{29} \left(\sum_{k \in s_h} w_k^{(l)} f_k - \sum_{k \in s_h} w_k f_k \right)^2$$

where k represents an NRI point, s_h is the set of NRI points in stratum h , $w_k^{(l)}$ represents the l^{th} replicate weight (area in ha) for NRI point k ($l = 1, \dots, 29$), and f_k represents the mean rate of change (g/ha) in soil organic carbon for the k^{th} point in the Monte Carlo analysis. The total variance is calculated by summing V_1 and V_2 .

For soil N_2O , DayCent cannot distinguish among the original sources of nitrogen after the mineral nitrogen enters the soil pools, and therefore it is not possible to determine which management activity led to specific N_2O emissions. This means, for example, that N_2O emissions from applied synthetic fertilizer cannot be separated from emissions due to other nitrogen inputs, such as crop residues. It is desirable, however, to report emissions associated with specific sources of nitrogen inputs. Thus, for each NRI survey location, the nitrogen inputs in a simulation are determined for anthropogenic practices discussed in IPCC (2006), including synthetic mineral nitrogen fertilization, organic amendments, and crop residue nitrogen added to soils (including nitrogen-fixing crops). The percentage of nitrogen input for anthropogenic practices is divided by the total nitrogen input, and this proportion is used to determine the amount of N_2O emissions assigned to each of the nitrogen sources. For example, if 70 percent of the mineral nitrogen made available in the soil is due to synthetic mineral fertilization, then 70 percent of the N_2O emissions are assigned to this practice.

A portion of soil N_2O emissions is reported under “other N inputs,” which includes mineralization due to decomposition of soil organic matter and litter, as well as asymbiotic nitrogen fixation from the atmosphere. Mineralization of soil organic matter is significant source of nitrogen, but is typically less than half of the amount of nitrogen made available in cropland soils compared to application of synthetic fertilizers and manure amendments. Mineralization of soil organic matter accounts for the majority of available nitrogen in grassland soils. Asymbiotic nitrogen fixation by soil bacteria is a minor source of nitrogen, typically not exceeding 10 percent of total nitrogen inputs. Accounting for the influence of “other N inputs” is necessary because the processes leading to these inputs of nitrogen are influenced by management.

This attribution of N_2O emissions to the individual nitrogen sources is required for reporting emissions based on UNFCCC reporting guidelines. However, this method is a simplification of reality to allow partitioning of N_2O emissions, as it

assumes that all nitrogen inputs have an identical chance of being converted to N₂O. It is important to realize that sources such as synthetic fertilization may have a larger impact on N₂O emissions than would be suggested by the associated level of nitrogen input for this source (Delgado et al. 2009). Further research will be needed to improve upon this attribution method, however.

For the land base that is simulated with the DayCent model, direct soil N₂O emissions are provided in Table A-182 and Table A-183.

Step 2b: Soil N₂O Emissions from Agricultural Lands on Mineral Soils Approximated with the Tier 1 Approach

To estimate direct N₂O emissions from nitrogen additions to crops in the Tier 1 method, the amount of nitrogen in applied synthetic fertilizer, manure, and other commercial organic fertilizers (i.e., dried blood, tankage, compost, and other) is added to nitrogen inputs from crop residues, and the resulting annual totals are multiplied by the IPCC default emission factor of 0.01 kg N₂O-N/kg N (IPCC 2006). The uncertainty is determined based on simple error propagation methods (IPCC 2006). The uncertainty in the default emission factor ranges from 0.3–3.0 kg N₂O-N/kg N (IPCC 2006). For flooded rice soils, the IPCC default emission factor is 0.003 kg N₂O-N/kg N and the uncertainty range is 0.000–0.006 kg N₂O-N/kg N (IPCC 2006).¹⁰⁶ Uncertainties in the emission factor and fertilizer additions are combined with uncertainty in the equations used to calculate residue nitrogen additions from above- and below-ground biomass dry matter and nitrogen concentration to derive overall uncertainty.

The Tier 1 method is also used to estimate emissions from manure nitrogen deposited by livestock on federal lands (i.e., PRP manure nitrogen), and from biosolids (i.e., treated sewage sludge) application to grasslands. These two sources of nitrogen inputs to soils are multiplied by the IPCC (2006) default emission factors (0.01 kg N₂O-N/kg N for sludge and horse, sheep, and goat manure, and 0.02 kg N₂O-N/kg N for cattle, swine, and poultry manure) to estimate N₂O emissions. The uncertainty is determined based on the simple error propagation methods provided by the IPCC (2006) with uncertainty in the default emission factor ranging from 0.007 to 0.06 kg N₂O-N/kg N (IPCC 2006).

The results for direct soil N₂O emissions using the Tier 1 method are provided in Table A-182 and Table A-183.

Step 2c: Soil CH₄ Emissions from Agricultural Lands Approximated with the Tier 1 Approach

To estimate CH₄ emissions from rice cultivation for the Tier 1 method, an adjusted daily emission factor is calculated using the default baseline emission factor of 1.30 kg CH₄ ha⁻¹ d⁻¹ (ranging 0.8-2.2 kg CH₄ ha⁻¹ d⁻¹) multiplied by a scaling factor for the cultivation water regime, pre-cultivation water regime and a scaling factor for organic amendments (IPCC 2006). The water regime during cultivation is continuously flooded for rice production in the United States and so the scaling factor is always 1 (ranging from 0.79 to 1.26). The pre-season water regime varies based on the proportion of land with winter flooding; land that does not have winter flooding is assigned a value of 0.68 (ranging from 0.58 to 0.80) and areas with winter flooding are assigned a value of 1 (ranging from 0.88 to 1.14). Organic amendments are estimated based on the amount of rice straw and multiplied by 1 (ranging 0.97 to 1.04) for rice straw residue incorporated greater than 30 days before cultivation, and by 0.29 (0.2 to 0.4) for rice straw residue incorporated greater than 30 days before cultivation. The adjusted daily emission factor is multiplied by the cultivation period and harvested area to estimate the total CH₄ emissions. The uncertainty is propagated through the calculation using an Approach 2 method with a Monte Carlo analysis (IPCC 2006), combining uncertainties associated with the adjusted daily emission factor and the harvested areas derived from the USDA NRI survey data.

The results for rice CH₄ emissions using the Tier 1 method are provided in Table A-179 and Table A-180.

Step 2d: Soil Organic Carbon Stock Changes in Agricultural Lands on Mineral Soils Approximated with the Tier 2 Approach

Mineral soil organic carbon stock values are derived for crop rotations that were not simulated by DayCent and land converted from non-agricultural land uses to cropland or grassland from 1990 through 2020, based on the land-use and management activity data in conjunction with appropriate reference carbon stocks, land-use change, management, input, and wetland restoration factors. Each quantity in the inventory calculations has uncertainty that is quantified in PDFs, including the land use and management activity data based on the six imputations in the data product combining CEAP, ARMS, Census of Agriculture, CTIC data and other related datasets (See Step 1b for more information); reference

¹⁰⁶ Due to lack of data, uncertainties are not addressed for managed manure nitrogen production, PRP manure nitrogen production, other commercial organic fertilizer amendments, indirect losses of nitrogen in the DayCent simulations, and biosolids (i.e., treated sewage sludge), but these sources of uncertainty will be included in future Inventories.

carbon stocks and stock change factors; and the replicated weights from the NRI survey. Uncertainty is estimated using two variance components (Ogle et al. 2010), as described in the section, Step 2a. In this case, a Monte Carlo Analysis is used to quantify uncertainty in soil organic carbon stock changes for the inventory period based on random selection of values from management data, reference carbon stocks and stock change factors. Input values are randomly selected from PDFs in an iterative process to estimate soil organic carbon change for 1,000 iterations in the analysis. This result is used to compute the first variance component. The second variance component is computed with the NRI replicate weights using a standard variance estimator for a two-stage sample design (Särndal *et al.* 1992). The two variance components are combined to produce a 95% confidence interval using simple error propagation methods provided by the IPCC (2006).

Derive Mineral Soil Organic Carbon Stock Change Factors: Stock change factors representative of U.S. conditions are estimated from published studies (Ogle et al. 2003; Ogle et al. 2006). The numerical factors quantify the impact of changing land use and management on soil organic carbon storage in mineral soils, including tillage practices, cropping rotation or intensification, and land conversions between cultivated and native conditions (including set-asides in the Conservation Reserve Program). Studies from the United States and Canada are used in this analysis under the assumption that they would best represent management impacts for the *Inventory*.

The IPCC inventory methodology for agricultural soils divides climate into eight distinct zones based upon average annual temperature, average annual precipitation, and the length of the dry season (IPCC 2006). Seven of these climate zones occur in the conterminous United States and Hawaii (Eve et al. 2001). Climate zones are classified using the IPCC climate map (IPCC 2006).

Soils are classified into one of seven mineral soil types based upon texture, morphology, and ability to store organic matter (IPCC 2006). Reference carbon stocks, representing estimates from conventionally managed cropland, are computed for each of the mineral soil types across the various climate zones, based on pedon (i.e., soil) data from the National Soil Survey Characterization Database (NRCS 1997) (Table A-179). These stocks are used in conjunction with management factors to estimate the change in soil organic carbon stocks that result from management and land-use activity. PDFs, which represent the variability in the stock estimates, are constructed as normal densities based on the mean and variance from the pedon data. Pedon locations are clumped in various parts of the country, which reduces the statistical independence of individual pedon estimates. To account for this lack of independence, samples from each climate by soil zone are tested for spatial autocorrelation using the Moran’s I test, and variance terms are inflated by 10 percent for all zones with significant p-values.

Table A-179: U.S. Soil Groupings Based on the IPCC Categories and Dominant Taxonomic Soil, and Reference Carbon Stocks (Metric Tons C/ha)

IPCC <i>Inventory</i> Soil Categories	USDA Taxonomic Soil Orders	Reference Carbon Stock in Climate Regions					
		Cold Temperate, Dry	Cold Temperate, Moist	Warm Temperate, Dry	Warm Temperate, Moist	Tropical, Dry	Tropical, Moist
High Clay Activity Mineral Soils	Vertisols, Mollisols, Inceptisols, Aridisols, and high base status Alfisols	42 (n = 133)	65 (n = 526)	37 (n = 203)	51 (n = 424)	42 (n = 26)	57 (n = 12)
Low Clay Activity Mineral Soils	Ultisols, Oxisols, acidic Alfisols, and many Entisols	45 (n = 37)	52 (n = 113)	25 (n = 86)	40 (n = 300)	39 (n = 13)	47 (n = 7)
Sandy Soils	Any soils with greater than 70 percent sand and less than 8 percent clay (often Entisols)	24 (n = 5)	40 (n = 43)	16 (n = 19)	30 (n = 102)	33 (n = 186)	50 (n = 18)
Volcanic Soils	Andisols	124 (n = 12)	114 (n = 2)	124 (n = 12)	124 (n = 12)	124 (n = 12)	128 (n = 9)
Spodic Soils	Spodosols	86 (n=20)	74 (n = 13)	86 (n=20)	107 (n = 7)	86 (n=20)	86 (n=20)
Aquic Soils	Soils with Aquic suborder	86 (n = 4)	89 (n = 161)	48 (n = 26)	51 (n = 300)	63 (n = 503)	48 (n = 12)

Notes: Carbon stocks are for the top 30 cm of the soil profile, and are estimated from pedon data available in the National Soil Survey Characterization database (NRCS 1997); sample size provided in parentheses (i.e., ‘n’ values refer to sample size).

To estimate the stock change factors for land use, management and input, studies had to report soil organic carbon stocks (or information to compute stocks), depth of sampling, and the number of years since a management change to

be included in the analysis. The data are analyzed using linear mixed-effect models, accounting for both fixed and random effects. Fixed effects included depth, number of years since a management change, climate, and the type of management change (e.g., reduced tillage vs. no-till). For depth increments, the data are not aggregated for the carbon stock measurements; each depth increment (e.g., 0-5 cm, 5-10 cm, and 10-30 cm) is included as a separate observation in the dataset. Similarly, time-series data are not aggregated in these datasets. Linear regression models assume that the underlying data are independent observations, but this is not the case with data from the same experimental site, or plot in a time series. These data are more related to each other than data from other sites (i.e., not independent). Consequently, random effects are needed to account for the dependence in time-series data and the dependence among data points representing different depth increments from the same study. Factors are estimated for the effect of management practices at 20 years for the top 30 cm of the soil (Table A-180). Variance is calculated for each of the country-specific factor values, and used to construct PDFs with a normal density. In the IPCC method, factor values are given for improved grassland, high input cropland with organic amendments, and for wetland rice, each of which influences carbon stock changes in soils. Specifically, higher stocks are associated with increased productivity and carbon inputs on improved grassland with both medium and high input.¹⁰⁷ Organic amendments in annual cropping systems also increase soil organic carbon stocks due to greater carbon inputs, while high soil organic carbon stocks in rice cultivation are associated with reduced decomposition due to periodic flooding. There are insufficient field studies to derive factor values for these systems from the published literature, and, thus, the factor values from IPCC (2006) are used under the assumption that they would best approximate the impacts, given the lack of data to derive country-specific factors. A measure of uncertainty is provided for these factors in IPCC (2006), which is used to construct PDFs.

Table A-180: Soil Organic Carbon Stock Change Factors for the United States and the IPCC Default Values Associated with Management Impacts on Mineral Soils

	IPCC default	U.S. Factor			
		Warm Moist Climate	Warm Dry Climate	Cool Moist Climate	Cool Dry Climate
Land-Use Change Factors					
Cultivated ^a	1	1	1	1	1
General Uncult ^{a,b} (n=251)	1.4	1.42±0.06	1.37±0.05	1.24±0.06	1.20±0.06
Set-Aside ^a (n=142)	1.25	1.31±0.06	1.26±0.04	1.14±0.06	1.10±0.05
Improved Grassland Factors					
Medium Input	1.1	1.14±0.06	1.14±0.06	1.14±0.06	1.14±0.06
High Input	NA	1.11±0.04	1.11±0.04	1.11±0.04	1.11±0.04
Wetland Rice Production Factor^b	1.1	1.1	1.1	1.1	1.1
Tillage Factors					
Conv. Till	1	1	1	1	1
Red. Till (n=93)	1.05	1.08±0.03	1.01±0.03	1.08±0.03	1.01±0.03
No-till (n=212)	1.1	1.13±0.02	1.05±0.03	1.13±0.02	1.05±0.03
Cropland Input Factors					
Low (n=85)	0.9	0.94±0.01	0.94±0.01	0.94±0.01	0.94±0.01
Medium	1	1	1	1	1
High (n=22)	1.1	1.07±0.02	1.07±0.02	1.07±0.02	1.07±0.02
High with amendment ^b	1.2	1.38±0.06	1.34±0.08	1.38±0.06	1.34±0.08

Note: The “n” values refer to sample size.

NA (Not Applicable)

^a Factors in the IPCC documentation (IPCC 2006) are converted to represent changes in soil organic carbon storage from a cultivated condition rather than a native condition.

^b U.S.-specific factors are not estimated for grassland improvements, rice production, or high input with amendment because of few studies addressing the impact of legume mixtures, irrigation, or manure applications for crop and grassland in the United States, or the impact of wetland rice production in the United States. Factors provided in IPCC (2006) are used as the best estimates of these impacts.

Wetland restoration management also influences soil organic carbon storage in mineral soils, because restoration leads to higher water tables and inundation of the soil for at least part of the year. A stock change factor is estimated assessing the difference in soil organic carbon storage between restored and unrestored wetlands enrolled in the Conservation

¹⁰⁷ Improved grasslands are identified in the NRI as grasslands that are irrigated or seeded with legumes, in addition to those reclassified as improved with manure amendments.

Reserve Program (Euliss and Gleason 2002), which represents an initial increase of carbon in the restored soils over the first 10 years (Table A-181). A PDF with a normal density is constructed from these data based on results from a linear regression model. Following the initial increase of carbon, natural erosion and deposition leads to additional accretion of carbon in these wetlands. The mass accumulation rate of organic carbon is estimated using annual sedimentation rates (cm/yr) in combination with percent organic carbon, and soil bulk density (g/cm³) (Euliss and Gleason 2002). Procedures for calculation of mass accumulation rate are described in Dean and Gorham (1998). The resulting rates and standard deviations are used to construct PDFs with a normal density (Table A-181).

Table A-181: Rate and standard deviation for the Initial Increase and Subsequent Annual Mass Accumulation Rate (Mg C/ha-yr) in Soil Organic Carbon Following Wetland Restoration of Conservation Reserve Program

Variable	Value
Factor (Initial Increase—First 10 Years)	1.22±0.18
Mass Accumulation (After Initial 10 Years)	0.79±0.05

Note: Mass accumulation rate represents additional gains in carbon for mineral soils after the first 10 years (Euliss and Gleason 2002).

Estimate Annual Changes in Mineral Soil Organic Carbon Stocks: In accordance with IPCC methodology, annual changes in mineral soil organic carbon are calculated by subtracting the beginning stock from the ending stock and then dividing by 20.¹⁰⁸ For this analysis, stocks are estimated for each year and difference between years is the stock change. From the final distribution of 1,000 values, the median is used as the estimate of soil organic carbon stock change and a 95 percent confidence interval is generated based on the simulated values at the 2.5 and 97.5 percentiles in the distribution.

Soil organic carbon stock changes using the Tier 2 method are provided in Table A-184 and Table A-186.

Step 2e: Estimate Additional Changes in Soil Organic Carbon Stocks Due to Biosolids (i.e., Treated Sewage Sludge) Amendments

There are two additional land use and management activities occurring on mineral soils of U.S. agricultural lands that are not estimated in Steps 2a and 2b. The first activity involves the application of biosolids to agricultural lands. Minimal data exist on where and how much biosolids are applied to U.S. agricultural soils. However, national estimates of mineral soil land area receiving biosolids can be approximated based on biosolids nitrogen production data, and the assumption that amendments are applied at a rate equivalent to the assimilative capacity from Kellogg et al. (2000). In this *Inventory*, it is assumed that biosolids for agricultural land application to soils is only used as an amendment in grassland. The impact of organic amendments on soil organic carbon is calculated as 0.38 metric tonnes C/ha-yr. This rate is based on the IPCC default method and country-specific factors, by calculating the effect of converting nominal, medium-input grassland to high input improved grassland. The assumptions for this estimation are as follows: a) the reference carbon stock is 50 metric tonnes C/ha, which represents a mid-range value of reference carbon stocks for the cropland soils in the United States,¹⁰⁹ b) the land use factor for grassland of 1.4 and 1.11 for high input improved grassland are representative of typical conditions, and c) the change in stocks are occurring over a 20 year (default value) time period (i.e., $[50 \times 1.4 \times 1.11 - 50 \times 1.4] / 20 = 0.38$). A ±50 percent uncertainty is attached to these estimates due to limited information on application and the rate of change in soil organic carbon stock change with amendments of biosolids.

The influence of biosolids (i.e., treated sewage sludge) on soil organic carbon stocks is provided in Table A-186.

Table A-182: Direct Soil N₂O Emissions from Mineral Soils in Cropland (MMT CO₂ Eq.)

Land Use Category	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Cropland Mineral Soil Emission	171.4	163.7	160.4	173.0	175.9	170.5	178.2	168.1	169.4	173.2
Tier 3 Cropland	151.4	144.8	140.5	153.0	153.9	149.7	155.6	147.8	148.0	149.2
Inorganic N Fertilizer Application	51.7	51.8	50.2	52.1	57.3	50.8	55.1	54.4	50.6	50.0
Managed Manure Additions	4.1	3.8	4.1	4.0	4.0	3.8	4.2	4.7	4.4	3.9
Crop Residue N	30.8	30.3	28.8	32.4	31.6	32.6	33.7	30.4	29.5	34.9

¹⁰⁸ The difference in carbon stocks is divided by 20 because the stock change factors represent change over a 20-year time period.

¹⁰⁹ Reference carbon stocks are based on cropland soils for the Tier 2 method applied in this *Inventory*.

Min. SOM / Asymbiotic N-Fixation ^a	64.8	58.9	57.5	64.5	60.9	62.5	62.6	58.3	63.5	60.5
Tier 1 Cropland	20.0	18.9	19.9	19.9	22.1	20.8	22.6	20.4	21.4	24.0
Inorganic N Fertilizer Application	9.3	8.2	9.2	9.4	11.0	9.8	11.8	10.1	10.8	13.1
Managed Manure Additions	7.4	7.5	7.5	7.5	7.8	8.0	7.8	7.3	7.5	8.0
Other Organic Amendments ^b	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0
Crop Residue N	3.3	3.1	3.2	3.0	3.2	3.0	3.0	2.9	3.0	2.9
Implied Emission Factor for Croplands ^c (kt N ₂ O-N/kt N)	0.015	0.014	0.014	0.015	0.015	0.015	0.015	0.014	0.014	0.014

Land Use Category	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Cropland Mineral Soil Emission	168.6	177.5	179.4	180.4	180.6	177.2	175.4	183.9	181.1	179.2
Tier 3 Cropland	149.4	157.8	159.7	161.1	159.6	158.2	154.6	164.0	160.9	163.6
Inorganic N Fertilizer Application	54.6	51.5	53.7	55.1	54.8	54.4	52.0	57.5	54.2	54.7
Managed Manure Additions	4.7	5.7	7.1	6.2	5.9	6.1	5.6	7.1	7.6	7.3
Crop Residue N	32.1	33.9	33.7	34.7	31.6	32.4	32.9	32.4	31.9	32.8
Min. SOM / Asymbiotic N-Fixation ^a	58.0	66.7	65.2	65.2	67.3	65.3	64.2	67.1	67.3	68.9
Tier 1 Cropland	19.2	19.6	19.7	19.3	21.0	19.0	20.8	19.9	20.1	15.6
Inorganic N Fertilizer Application	8.9	10.0	10.8	9.8	11.8	9.9	11.0	11.1	11.7	7.2
Managed Manure Additions	7.4	6.8	6.2	6.7	6.5	6.5	7.2	6.2	6.0	5.9
Other Organic Amendments ^b	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0
Crop Residue N	2.9	2.8	2.6	2.7	2.7	2.6	2.5	2.5	2.5	2.5
Implied Emission Factor for Croplands ^c (kt N ₂ O-N/kt N)	0.014	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015

Land Use Category	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Cropland Mineral Soil Emission	181.9	185.6	176.0	200.2	206.6	195.5	186.7	192.6	205.9	190.5
Tier 3 Cropland	164.3	165.5	158.1	180.1	187.3	176.3	169.5	173.4	187.7	169.9
Inorganic N Fertilizer Application	52.8	55.9	60.4	62.0	63.4	58.3	58.1	58.9	61.5	54.7
Managed Manure Additions	7.5	8.2	7.9	8.5	8.7	8.1	7.8	8.1	8.2	7.8
Crop Residue N	33.9	35.9	32.4	35.0	36.8	32.9	30.5	33.8	36.7	31.7
Min. SOM / Asymbiotic N-Fixation ^a	70.1	65.5	57.3	74.6	78.5	76.9	73.0	72.6	81.3	75.7
Tier 1 Cropland	17.5	20.1	17.9	20.1	19.3	19.3	17.2	19.2	18.2	20.6
Inorganic N Fertilizer Application	9.6	12.2	9.9	12.1	11.2	10.9	8.5	10.2	8.8	11.0
Managed Manure Additions	5.5	5.5	5.6	5.5	5.5	5.8	5.9	6.3	6.5	6.7
Other Organic Amendments ^b	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.1	0.1
Crop Residue N	2.5	2.4	2.4	2.5	2.6	2.6	2.6	2.6	2.8	2.8
Implied Emission Factor for Croplands ^c (kt N ₂ O-N/kt N)	0.014	0.015	0.014	0.015	0.016	0.015	0.014	0.015	0.015	0.014

Land Use Category	2020
Total Cropland Mineral Soil Emission	179.5
Tier 3 Cropland	160.5
Inorganic N Fertilizer Application	53.8
Managed Manure Additions	7.6
Crop Residue N	34.7
Min. SOM / Asymbiotic N-Fixation ^a	64.3
Tier 1 Cropland	19.0
Inorganic N Fertilizer Application	9.4
Managed Manure Additions	6.7
Other Organic Amendments ^b	0.1
Crop Residue N	2.9
Implied Emission Factor for Croplands ^c (kt N ₂ O-N/kt N)	0.014

Managed Manure Additions	0.0
Pasture, Range, & Paddock N Deposition	7.4
Grass Residue N	28.2
Min. SOM / Asymbiotic N-Fixation ^a	36.2
Tier 1 Grassland	6.2
Pasture, Range, & Paddock N Deposition	5.9
Treated Sewage Sludge Additions	0.4
Implied Emission Factor for Grassland ^b (kt N ₂ O-N/kt N)	0.006

^a Mineralization of soil organic matter and the asymbiotic fixation of nitrogen gas.

^b Annual Implied Emission Factors (kt N₂O-N/kt N) are calculated by dividing total estimated emissions by total activity data for N applied.

Note: Emissions in 2021 and 2022 are mostly estimated with a data splicing method as described in the agricultural soil management section of the NIR. Additional activity data will be collected, and the Tier 1 and 3 methods will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Table A-184: Annual Change in Soil Organic Carbon Stocks in Croplands (MMT CO₂ Eq./yr)

Land Use Change Category	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Cropland Soil Organic C Stock Change	-16.0	-27.7	-38.5	-27.6	-34.9	-29.7	-51.9	-48.4	-45.8	-41.2
Cropland Remaining Cropland (CRC)	-39.2	-52.2	-59.5	-45.9	-53.1	-49.8	-69.6	-66.5	-61.3	-59.1
Tier 2	-1.6	-2.9	-3.6	-3.6	-3.1	-3.1	-2.9	-4.0	-3.4	-3.8
Tier 3	-37.6	-49.3	-55.9	-42.3	-50.0	-46.7	-66.8	-62.5	-57.9	-55.3
Grassland Converted to Cropland (GCC)	24.6	26.1	22.8	20.3	20.2	22.1	19.8	20.4	17.8	20.2
Tier 2	3.1	3.3	3.1	3.0	3.3	3.6	3.9	3.8	3.9	3.8
Tier 3	21.5	22.8	19.7	17.3	16.9	18.5	15.9	16.6	14.0	16.4
Forest Converted to Cropland (FCC) (Tier 2 Only)	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Other Lands Converted to Cropland (OCC) (Tier 2 Only)	-1.9	-2.1	-2.2	-2.4	-2.5	-2.5	-2.6	-2.7	-2.7	-2.8
Settlements Converted to Cropland (SCC) (Tier 2 Only)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2
Wetlands Converted to Cropland (WCC) (Tier 2 Only)	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3

Land Use Change Category	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Cropland Soil Organic C Stock Change	-50.3	-53.5	-56.1	-46.6	-52.6	-50.5	-49.0	-46.1	-56.0	-36.7
Cropland Remaining Cropland (CRC)	-64.7	-66.1	-68.3	-59.1	-64.1	-61.8	-58.3	-56.6	-63.4	-45.0
Tier 2	-3.2	-3.5	-5.2	-4.6	-4.2	-4.4	-3.6	-3.6	-3.3	-3.5
Tier 3	-61.5	-62.5	-63.0	-54.5	-59.9	-57.5	-54.6	-53.0	-60.0	-41.5
Grassland Converted to Cropland (GCC)	17.2	15.3	14.8	15.0	13.9	13.7	11.6	12.6	9.4	10.2
Tier 2	3.9	4.1	3.9	3.7	3.8	3.8	3.6	3.7	3.6	3.5
Tier 3	13.2	11.2	10.9	11.3	10.1	9.9	8.0	8.9	5.8	6.7
Forest Converted to Cropland (FCC) (Tier 2 Only)	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
Other Lands Converted to Cropland (OCC) (Tier 2 Only)	-3.1	-3.1	-3.0	-2.8	-2.7	-2.6	-2.6	-2.3	-2.2	-2.1
Settlements Converted to Cropland (SCC) (Tier 2 Only)	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Wetlands Converted to Cropland (WCC) (Tier 2 Only)	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2

Land Use Change Category	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Cropland Soil Organic C Stock Change	-39.6	-61.1	-47.7	-35.0	-42.7	-43.0	-40.6	-37.8	-38.0	-39.9
Cropland Remaining Cropland (CRC)	-49.2	-67.8	-56.4	-45.3	-51.6	-53.3	-51.6	-47.8	-47.1	-48.5
Tier 2	-3.8	-3.2	-3.0	-3.8	-4.1	-4.5	-4.3	-4.2	0.2	-1.7
Tier 3	-45.5	-64.6	-53.4	-41.5	-47.6	-48.8	-47.3	-43.6	-47.4	-46.8
Grassland Converted to Cropland (GCC)	11.6	8.6	10.6	12.2	10.7	12.0	12.8	11.8	10.7	10.1

Tier 2	3.5	3.6	3.6	3.5	3.4	3.3	3.2	3.0	3.0	2.7
Tier 3	8.1	5.0	7.0	8.7	7.3	8.7	9.6	8.8	7.7	7.4
Forest Converted to Cropland (FCC) (Tier 2 Only)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Other Lands Converted to Cropland (OCC) (Tier 2 Only)	-2.1	-2.1	-2.1	-2.0	-1.9	-1.9	-1.9	-1.9	-1.7	-1.6
Settlements Converted to Cropland (SCC) (Tier 2 Only)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2
Wetlands Converted to Cropland (WCC) (Tier 2 Only)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

Land Use Change Category	2020
Total Cropland Soil Organic C Stock Change	-31.3
Cropland Remaining Cropland (CRC)	-38.2
Tier 2	-1.9
Tier 3	-36.3
Grassland Converted to Cropland (GCC)	8.0
Tier 2	2.5
Tier 3	5.5
Forest Converted to Cropland (FCC) (Tier 2 Only)	0.1
Other Lands Converted to Cropland (OCC) (Tier 2 Only)	-1.2
Settlements Converted to Cropland (SCC) (Tier 2 Only)	-0.2
Wetlands Converted to Cropland (WCC) (Tier 2 Only)	0.2

Note: Emissions in 2021 and 2022 are mostly estimated with a data splicing method as described in the cropland remaining croplands section of the *Inventory*. Additional activity data will be collected, and the Tier 1 and 3 methods will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Table A-185: Annual Change in Soil Organic Carbon Stocks in Grasslands (MMT CO₂ Eq./yr)

Land Use Change Category	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Grassland Soil Organic C Stock Change	4.1	6.5	2.3	0.2	-18.6	-6.2	-17.3	4.1	-14.2	-2.3
Grassland Remaining Grassland (GRG)	18.6	21.4	17.8	17.6	1.3	13.4	3.8	25.5	11.1	22.2
Tier 2	-0.2	-0.3	-0.5	-0.3	-0.0	-0.0	0.0	-0.0	0.0	0.1
Tier 3	19.5	22.3	18.9	18.6	2.1	14.2	4.6	26.4	12.0	23.1
Treated Sewage Sludge Additions	-0.6	-0.6	-0.7	-0.7	-0.8	-0.8	-0.8	-0.9	-0.9	-0.9
Cropland Converted to Grassland (CCG)	-10.4	-10.6	-10.9	-11.9	-13.5	-12.9	-14.1	-14.2	-17.6	-16.6
Tier 2	-3.9	-3.8	-3.8	-4.1	-4.4	-4.3	-4.2	-4.0	-4.7	-4.7
Tier 3	-6.6	-6.7	-7.1	-7.9	-9.1	-8.6	-10.0	-10.2	-12.9	-11.9
Forest Converted to Grassland (FCG) (Tier 2 Only)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Other Lands Converted to Grassland (OCG) (Tier 2 Only)	-3.8	-4.0	-4.3	-5.2	-6.1	-6.4	-6.6	-6.9	-7.3	-7.5
Settlements Converted to Grassland (SCG) (Tier 2 Only)	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3
Wetlands Converted to Grassland (WCG) (Tier 2 Only)	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0

Land Use Change Category	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Grassland Soil Organic C Stock Change	-34.9	-18.3	-15.3	-17.4	-15.1	-9.4	-26.2	-9.8	-23.4	-18.8
Grassland Remaining Grassland (GRG)	-7.2	9.9	13.3	10.8	13.8	18.6	3.0	18.1	4.6	7.5
Tier 2	-0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2
Tier 3	-6.2	10.9	14.3	11.7	14.7	19.5	3.9	19.1	5.5	8.4

Treated Sewage Sludge Additions	-1.0	-1.0	-1.0	-1.0	-1.1	-1.1	-1.1	-1.1	-1.1	-1.1
Cropland Converted to Grassland (CCG)	-18.5	-18.5	-18.9	-18.5	-19.2	-18.1	-19.4	-18.0	-18.0	-16.2
Tier 2	-4.8	-4.7	-4.6	-4.4	-4.3	-4.1	-3.9	-3.6	-3.5	-3.1
Tier 3	-13.8	-13.8	-14.2	-14.1	-14.8	-14.0	-15.4	-14.4	-14.5	-13.1
Forest Converted to Grassland (FCG) (Tier 2 Only)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Other Lands Converted to Grassland (OCG) (Tier 2 Only)	-8.7	-9.3	-9.3	-9.3	-9.3	-9.4	-9.4	-9.4	-9.5	-9.6
Settlements Converted to Grassland (SCG) (Tier 2 Only)	-0.3	-0.3	-0.4	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.4
Wetlands Converted to Grassland (WCG) (Tier 2 Only)	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0

Land Use Change Category	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Grassland Soil Organic C Stock										
Change	-5.0	-20.1	-23.6	-7.3	-1.0	-8.5	11.7	-1.7	-0.4	-0.1
Grassland Remaining Grassland (GRG)	21.6	6.2	4.4	19.3	23.4	18.5	36.1	22.4	22.0	22.0
Tier 2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.1	0.1
Tier 3	22.4	7.1	5.4	20.2	24.4	19.5	37.1	23.4	22.9	22.9
Treated Sewage Sludge Additions	-1.1	-1.1	-1.1	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
Cropland Converted to Grassland (CCG)	-16.6	-16.1	-15.0	-14.4	-12.9	-14.7	-12.7	-13.0	-11.7	-11.1
Tier 2	-3.1	-2.9	-2.9	-2.7	-2.2	-2.2	-2.1	-2.2	-1.9	-2.0
Tier 3	-13.5	-13.1	-12.1	-11.7	-10.7	-12.5	-10.6	-10.8	-9.8	-9.1
Forest Converted to Grassland (FCG) (Tier 2 Only)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Other Lands Converted to Grassland (OCG) (Tier 2 Only)	-9.6	-9.7	-12.4	-11.5	-10.9	-11.8	-11.0	-10.5	-10.1	-10.4
Settlements Converted to Grassland (SCG) (Tier 2 Only)	-0.4	-0.4	-0.5	-0.6	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
Wetlands Converted to Grassland (WCG) (Tier 2 Only)	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0

Land Use Change Category	2020
Total Grassland Soil Organic C Stock	
Change	-9.4
Grassland Remaining Grassland (GRG)	9.3
Tier 2	0.1
Tier 3	10.2
Treated Sewage Sludge Additions	-1.0
Cropland Converted to Grassland (CCG)	-10.1
Tier 2	-1.8
Tier 3	-8.3
Forest Converted to Grassland (FCG) (Tier 2 Only)	-0.1
Other Lands Converted to Grassland (OCG) (Tier 2 Only)	-8.1
Settlements Converted to Grassland (SCG) (Tier 2 Only)	-0.4
Wetlands Converted to Grassland (WCG) (Tier 2 Only)	-0.0

Note: Emissions in 2021 and 2022 are mostly estimated with a data splicing method as described in the cropland remaining croplands section of the *Inventory*. Additional activity data will be collected, and the Tier 1 and 3 methods will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Table A-186: Methane Emissions from Rice Cultivation (MMT CO₂ Eq.)

Approach	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Rice Methane Emission	18.9	19.5	19.0	19.1	18.1	19.1	19.7	17.9	20.4	19.0
Tier 1	3.0	3.0	3.0	2.9	3.0	2.8	2.9	2.9	3.3	4.2
Tier 3	15.9	16.5	16.0	16.2	15.1	16.3	16.8	15.0	17.2	14.8

Approach	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Rice Methane Emission	22.4	19.0	21.5	17.9	17.6	20.6	18.0	18.5	16.4	19.6
Tier 1	5.2	3.9	3.3	3.1	2.7	2.7	2.5	3.0	2.4	3.2
Tier 3	17.3	15.1	18.2	14.8	14.9	17.8	15.5	15.5	14.0	16.4

Approach	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Rice Methane Emission	21.5	19.4	17.7	18.1	17.6	19.6	19.9	16.7	19.9	15.6
Tier 1	2.8	2.9	3.0	3.0	3.1	2.8	3.2	2.4	3.0	2.6
Tier 3	18.7	16.5	14.7	15.0	14.5	16.8	16.7	14.3	16.9	13.0

Approach	2020
Total Rice Methane Emission	18.6
Tier 1	2.9
Tier 3	15.7

Emissions in 2021 and 2022 are mostly estimated with a data splicing method as described in the cropland remaining croplands section of the *Inventory*. Additional activity data will be collected, and the Tier 1 and 3 methods will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Step 3: Estimate Soil Organic Carbon Stock Changes and Direct N₂O Emissions from Organic Soils

In this step, soil organic carbon losses and direct N₂O emissions are estimated for organic soils that are drained for agricultural production in croplands and grasslands.

Step 3a: Direct N₂O Emissions Due to Drainage of Organic Soils in Cropland and Grassland

To estimate annual N₂O emissions from drainage of organic soils in cropland and grassland, the area of drained organic soils for temperate regions is multiplied by the IPCC (2006) default emission factor for temperate soils and the corresponding area in sub-tropical regions is multiplied by the average (12 kg N₂O-N/ha cultivated) of IPCC (2006) default emission factors for temperate (8 kg N₂O-N/ha cultivated) and tropical (16 kg N₂O-N/ha cultivated) organic soils. The uncertainty is determined based on simple error propagation methods (IPCC 2006), including uncertainty in the default emission factor ranging from 2–24 kg N₂O-N/ha (IPCC 2006). Table A-187 lists the direct N₂O emissions associated with drainage of organic soils in cropland and grassland.

Table A-187: Direct Soil N₂O Emissions from Drainage of Organic Soils (MMT CO₂ Eq.)

Land Use	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Organic Soil Emissions	5.7	5.7	5.7	5.7	5.7	5.7	5.6	5.7	5.6	5.6
Cropland	3.4	3.4	3.4	3.3	3.3	3.3	3.3	3.3	3.3	3.3
Grassland	2.3	2.3	2.3	2.3	2.4	2.3	2.3	2.4	2.3	2.3

Land Use	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Organic Soil Emission	5.6	5.6	5.6	5.4	5.5	5.5	5.5	5.4	5.4	5.4
Cropland	3.3	3.3	3.3	3.2	3.3	3.2	3.2	3.1	3.1	3.0
Grassland	2.3	2.3	2.3	2.2	2.2	2.2	2.3	2.2	2.3	2.3

Land Use	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Organic Soil Emission	5.4	5.4	5.3	5.3	5.3	5.3	5.3	5.2	5.2	5.1

Cropland	3.0	3.1	3.1	3.1	3.0	3.0	3.0	3.0	3.0	2.9
Grassland	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.2	2.2	2.2

Land Use	2020
Total Organic Soil Emission	5.2
Cropland	2.9
Grassland	2.2

Note: Emissions in 2021 and 2022 are estimated with a data splicing method as described in the agricultural soil management section of the *Inventory*. Additional activity data will be collected, and the Tier 1 method will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Step 3b: Soil Organic Carbon Stock Changes Due to Drainage of Organic Soils in Cropland and Grassland

Change in soil organic carbon stocks due to drainage of organic soils in cropland and grassland are estimated annually from 1990 through 2020, based on the land-use and management activity data in conjunction with appropriate emission factors. The activity data are based on annual data from 1990 through 2020 from the NRI. Organic soil emission factors that are representative of U.S. conditions have been estimated from published studies (Ogle et al. 2003), based on subsidence studies in the United States and Canada (Table A-188). PDFs are constructed as normal densities based on the mean carbon loss rates and associated variances. Uncertainty is estimated using two variance components (Ogle et al. 2010), as described in the section, Step 2a for the first variance component, input values are randomly selected from PDFs in a Monte Carlo analysis to estimate soil organic carbon change for 1,000 iterations. The second variance component is computed with the NRI replicate weights using a standard variance estimator for a two-stage sample design (Särndal et al. 1992). The two variance components are combined to produce a 95% confidence interval using simple error propagation methods provided by the IPCC (2006). Losses of soil organic carbon from drainage of cropland and grassland soils are provided in Table A-189 for croplands and Table A-190 for grasslands.

Table A-188: Carbon Loss Rates for Organic Soils Under Agricultural Management in the United States, and IPCC Default Rates (Metric Ton C/ha-yr)

Region	Cropland		Grassland	
	IPCC	U.S. Revised	IPCC	U.S. Revised
Cold Temperate, Dry & Cold Temperate, Moist	1	11.2±2.5	0.25	2.8±0.5 ^a
Warm Temperate, Dry & Warm Temperate, Moist	10	14.0±2.5	2.5	3.5±0.8 ^a
Tropical, Dry & Tropical, Moist	1	14.3±2.5	0.25	2.8±0.5 ^a

^a There are not enough data available to estimate a U.S. value for carbon losses from grassland. Consequently, estimates are 25 percent of the values for cropland, which is an assumption that is used for the IPCC default organic soil carbon losses on grassland.

Table A-189: Soil Organic Carbon Stock Changes due to Drainage of Organic Soils in Cropland (MMT CO₂ Eq.)

Land Use Category	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Cropland Soil Organic C Stock Change	37.3	36.7	35.9	35.7	35.0	35.1	35.0	35.0	34.8	30.8
Cropland Remaining Cropland (CRC)	34.2	33.6	32.8	32.3	31.7	31.6	31.5	31.5	31.0	26.9
Grassland Converted to Cropland (GCC)	2.4	2.4	2.4	2.6	2.5	2.7	2.7	2.6	3.0	3.1
Forest Converted to Cropland (FCC)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Other Lands Converted to Cropland (OCC)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Settlements Converted to Cropland (SCC)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Wetlands Converted to Cropland (WCC)	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6

Land Use Category	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Cropland Soil Organic C Stock Change	30.5	34.5	34.4	34.2	34.2	34.1	33.7	33.3	33.1	32.6
Cropland Remaining Cropland (CRC)	26.7	30.3	30.2	30.1	30.3	30.2	30.0	29.6	29.6	29.4
Grassland Converted to Cropland (GCC)	3.1	3.6	3.6	3.5	3.3	3.3	3.1	3.2	3.0	2.7
Forest Converted to Cropland (FCC)	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Other Lands Converted to Cropland (OCC)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Settlements Converted to Cropland (SCC)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Cropland Converted to Grassland (CCG)	1.0
Forest Converted to Grassland (FCG)	0.1
Other Lands Converted to Grassland (OCG)	0.1
Settlements Converted to Grassland (SCG)	0.0
Wetlands Converted to Grassland (WCG)	0.2

Note: Emissions in 2021 and 2022 are estimated with a data splicing method as described in the grassland remaining grassland section of the *Inventory*. Additional activity data will be collected, and the Tier 2 method will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Step 4: Estimate Indirect Soil N₂O Emissions for Croplands and Grasslands

In this step, soil N₂O emissions are estimated for the two indirect emission pathways (N₂O emissions due to volatilization, and N₂O emissions due to leaching and runoff of N), which are summed to yield total indirect N₂O emissions from croplands and grasslands.

Step 4a: Indirect Soil N₂O Emissions Due to Volatilization

Indirect emissions from volatilization of nitrogen inputs from synthetic fertilizer, manure amendments, and PRP manure, are calculated according to the amount of mineral nitrogen that is volatilized from the soil profile and later emitted as soil N₂O following atmospheric deposition. See Step 1d for additional information about the methods used to compute nitrogen losses due to volatilization. The estimated nitrogen volatilized is multiplied by the IPCC default emission factor of 0.01 kg N₂O-N/kg N (IPCC 2006) to estimate total indirect soil N₂O emissions from volatilization. The uncertainty is estimated using simple error propagation methods (IPCC 2006), by combining uncertainties in the amount of nitrogen volatilized, with uncertainty in the default emission factor ranging from 0.002–0.05 kg N₂O-N/kg N (IPCC 2006). See the following peer-reviewed publications on the use of DayCent for estimating the nitrogen losses that lead to indirect soil N₂O emissions: Del Grosso et al. (2001; 2005; 2008b; 2010; 2011), Delgado et al. (2009) and Scheer et al. (2013). The estimates and implied emission factors are provided in Table A-191 and for cropland and grassland, respectively.

Step 4b: Indirect Soil N₂O Emissions Due to Leaching and Runoff

The amounts of mineral nitrogen from synthetic fertilizers, manure amendments, PRP manure, crop residue, nitrogen mineralization, asymbiotic fixation that is transported from the soil profile in water flows are used to calculate indirect emissions from leaching of mineral nitrogen from soils and losses in runoff associated with overland flow. See Step 1d for additional information about the methods used to estimate nitrogen losses from soils due to leaching and runoff in overland water flows. The total amount of nitrogen transported from soil profiles through leaching and surface runoff is multiplied by the IPCC default emission factor of 0.0075 kg N₂O-N/kg N (IPCC 2006) to estimate emissions for this source. The uncertainty is quantified based on simple error propagation methods (IPCC 2006), including uncertainty in the default emission factor ranging from 0.0005 to 0.025 kg N₂O-N/kg N (IPCC 2006). The emission estimates are provided in Table A-191 and Table A-192 for cropland and grassland, respectively.

Table A-191: Indirect Soil N₂O Emissions for Cropland from Volatilization and Atmospheric Deposition, and from Leaching and Runoff (MMT CO₂ Eq.)

Source	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Cropland Indirect Emissions	23.6	21.5	23.2	25.7	20.8	23.4	23.3	22.0	25.2	23.5
Volatilization & Atmospheric Deposition	6.6	6.3	6.1	6.4	6.8	6.7	6.8	6.6	7.0	7.1
Leaching & Runoff	17.0	15.2	17.1	19.3	14.1	16.7	16.5	15.4	18.2	16.4
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Cropland Indirect Emissions	21.4	23.9	21.7	22.6	25.6	22.3	23.5	24.6	25.3	24.1
Volatilization & Atmospheric Deposition	7.0	6.8	6.9	6.9	7.1	7.0	7.1	6.9	6.9	6.6
Leaching & Runoff	14.4	17.0	14.8	15.6	18.5	15.3	16.4	17.7	18.4	17.5
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
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Total Cropland Indirect Emissions	24.7	24.3	19.4	26.5	26.5	28.8	25.0	26.3	28.1	28.0
Volatilization & Atmospheric Deposition	7.0	6.9	6.6	7.2	7.4	7.4	7.4	7.4	7.9	7.1
Leaching & Runoff	17.7	17.3	12.7	19.3	19.0	21.3	17.6	18.9	20.3	20.9
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2020
Total Cropland Indirect Emissions	23.3
Volatilization & Atmospheric Deposition	7.5
Leaching & Runoff	15.8
Volatilization Implied Emission Factor	0.0100
Leaching & Runoff Implied Emission Factor	0.0075

Note: Emissions in 2021 and 2022 are estimated with a data splicing method as described in the agricultural soil management section of the *Inventory*. Additional activity data will be collected, and the Tier 1 method will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Table A-192: Indirect Soil N₂O Emissions for Grassland from Volatilization and Atmospheric Deposition, and from Leaching and Runoff (MMT CO₂ Eq.)

Source	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Grassland Indirect Emissions	6.4	6.3	6.4	6.6	6.3	6.4	6.3	6.4	7.0	6.2
Volatilization & Atmospheric Deposition	3.4	3.4	3.4	3.3	3.4	3.4	3.5	3.4	3.5	3.3
Leaching & Runoff	2.9	2.9	3.0	3.3	2.9	3.0	2.8	2.9	3.5	2.9
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Grassland Indirect Emissions	5.6	6.6	6.4	6.1	6.8	6.1	6.2	6.6	6.5	6.5
Volatilization & Atmospheric Deposition	3.1	3.3	3.4	3.4	3.5	3.4	3.4	3.3	3.3	3.3
Leaching & Runoff	2.5	3.3	3.0	2.7	3.3	2.7	2.8	3.3	3.2	3.2
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total Grassland Indirect Emissions	6.3	6.2	5.7	6.5	6.0	6.7	6.2	6.3	7.0	6.8
Volatilization & Atmospheric Deposition	3.3	3.1	3.1	3.4	3.4	3.3	3.3	3.3	3.3	3.2
Leaching & Runoff	3.0	3.1	2.6	3.2	2.6	3.4	2.8	3.0	3.7	3.6
Volatilization Implied Emission Factor	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Leaching & Runoff Implied Emission Factor	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075

Source	2020
Total Grassland Indirect Emissions	6.1
Volatilization & Atmospheric Deposition	3.0
Leaching & Runoff	3.1
Volatilization Implied Emission Factor	0.0100
Leaching & Runoff Implied Emission Factor	0.0075

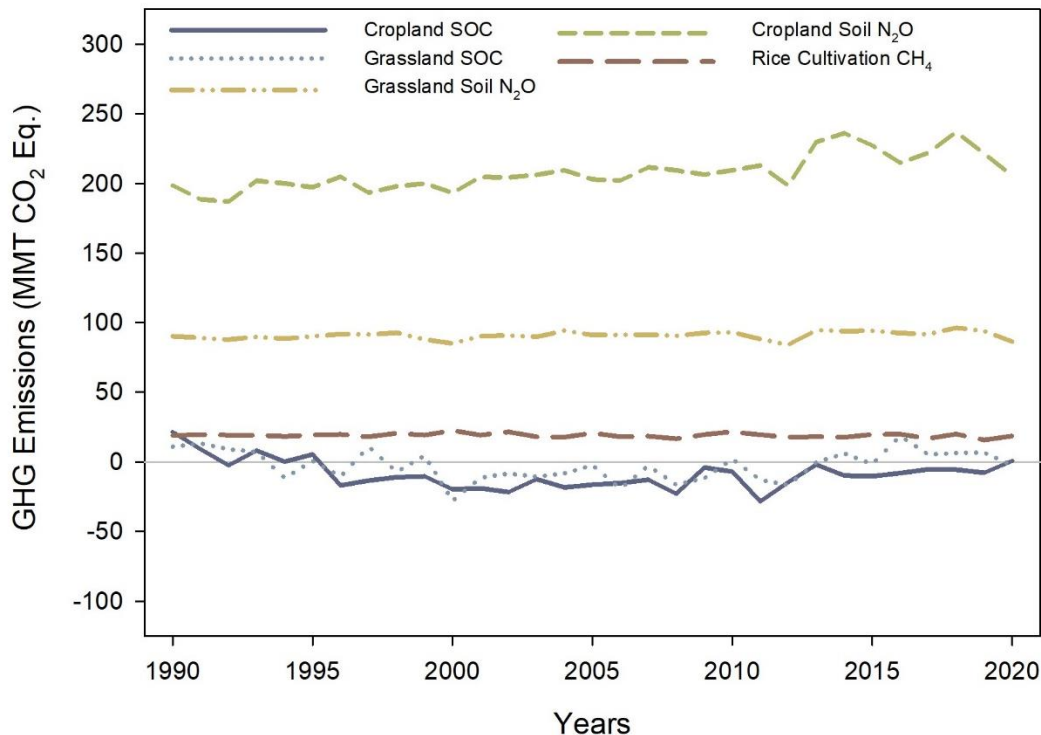
Note: Emissions in 2021 and 2022 are estimated with a data splicing method as described in the agricultural soil management section of the *Inventory*. Additional activity data will be collected, and the Tier 1 method will be applied in a future *Inventory* to recalculate the part of the time series that is estimated with the data splicing methods.

Step 5: Estimate Total Emissions for U.S. Agricultural Soils

Total N₂O emissions are estimated by summing total direct and indirect emissions for croplands and grasslands with organic and mineral soils based on the Tier 1 and 3 methods. Total soil organic carbon stock changes are estimated by summing changes in mineral and organic soils for cropland remaining cropland, land converted to cropland, grassland

remaining grassland, and land converted to grassland based on the Tier 2 and 3 methods. Total rice CH₄ emissions are estimated by summing results from the Tier 1 and 3 methods. The results are provided in Figure A-9. In general, N₂O emissions from agricultural soil management have been relatively stable for grasslands and increasing slightly for croplands from 1990 to 2020, while CH₄ emissions from rice cultivation have been relatively stable. Agricultural soil organic carbon stocks have increased for most years in croplands and grasslands leading to sequestration of carbon in soils.

Figure A-9: Greenhouse Gas Emissions and Removals for Cropland & Grassland



Direct and indirect simulated emissions of soil N₂O vary regionally in croplands and grasslands as a function of N input, other management practices, weather, and soil type. The top-5 highest total N₂O emissions for 2020¹¹⁰ occur in Illinois, Iowa, Kansas, Nebraska, and Texas (Table A-175). These areas are in the Midwestern Corn Belt region, which is the largest crop producing region in the country, and/or have a large population of grazing livestock with high levels of PRP manure nitrogen inputs. The states with largest increases in soil organic carbon stocks in 2020 include Illinois, Iowa, Kansas, Missouri, and Nebraska (Table A-193). These states tend to have larger amounts of land conversion to grassland and/or more conservation practices such as enrollment in Conservation Reserve Program or adoption of conservation tillage. For rice cultivation, the states with highest CH₄ emissions are Arkansas, California, Louisiana and Texas (Table A-193). These states also have the largest areas of rice cultivation, and Louisiana and Texas have a relatively large proportion of fields with a second ratoon crop each year. Ratoon crops extend the period of flooding, and with the residues left from the initial rice crop, there are additional CH₄ emissions compared to non-ratoon rice management systems.

¹¹⁰ The emissions data at the state scale are available for 1990 to 2020 from application of the inventory methods described in this annex. A data splicing method has been applied to estimate emissions at the national scale for 2021 to 2022. Therefore, the final year of emissions data at the state scale is 2020.

Table A-193: Total Soil N₂O Emissions (Direct and Indirect), Soil Organic Carbon Stock Changes and Rice CH₄ Emissions from Agricultural Lands by State in 2020 (MMT CO₂ Eq.)

State	N ₂ O Emissions		Soil Organic C Stock Change		Rice	Total Emissions
	Croplands	Grasslands	Croplands	Grasslands	CH ₄	
AL	1.30	0.96	-0.38	0.62	0.00	1.26
AK ^a	0.00	0.01	NE	NE	NE	0.01
AZ	0.74	2.92	-0.09	0.57	0.00	4.13
AR	4.62	1.22	-0.18	-0.48	6.82	12.00
CA	5.72	2.37	0.52	-0.26	3.62	11.96
CO	3.63	3.64	-0.50	-0.86	0.00	5.91
CT	0.08	0.02	-0.01	-0.04	0.00	0.05
DE	0.24	0.02	-0.24	-0.02	0.00	0.00
DC	NE	NE	NE	NE	NE	NE
FL	2.04	2.14	10.70	0.45	0.00	15.32
GA	1.85	0.75	0.02	-0.34	0.00	2.27
HI ^a	0.01	0.07	0.20	0.37	0.00	0.65
ID	3.62	1.42	-0.44	0.19	0.00	4.80
IL	15.39	0.76	-1.64	-0.73	0.00	13.78
IN	7.92	0.51	1.76	-0.35	0.00	9.85
IA	18.65	1.46	-3.01	-3.07	0.00	14.03
KS	14.21	4.17	-3.91	-2.52	0.00	11.95
KY	2.94	1.51	-1.16	-0.71	0.00	2.57
LA	3.40	0.89	0.75	-0.22	3.65	8.48
ME	0.18	0.05	-0.05	-0.06	0.00	0.13
MD	0.62	0.14	-0.69	-0.11	0.00	-0.04
MA	0.10	0.04	0.22	-0.03	0.00	0.33
MI	4.04	0.79	2.24	0.05	0.00	7.12
MN	13.34	1.82	6.31	1.12	0.00	22.59
MS	3.18	0.79	0.37	-0.25	0.60	4.69
MO	8.45	2.62	-1.13	-1.53	0.96	9.36
MT	5.33	6.54	-0.89	8.79	0.00	19.78
NE	13.57	3.90	-3.52	-2.56	0.00	11.39
NV	0.22	0.85	0.01	0.07	0.00	1.14
NH	0.04	0.03	0.01	-0.02	0.00	0.07
NJ	0.20	0.05	0.03	-0.09	0.00	0.19
NM	0.79	4.57	0.02	2.60	0.00	7.98
NY	2.21	0.77	-0.62	-0.31	0.00	2.04
NC	2.77	0.56	1.04	-0.41	0.00	3.96
ND	11.92	2.25	-1.03	-0.45	0.00	12.69
OH	6.12	0.64	-0.84	-0.67	0.00	5.25
OK	3.63	4.30	-0.09	-1.26	0.00	6.58
OR	1.99	1.58	0.00	0.77	0.00	4.34
PA	2.12	0.60	-1.78	-0.59	0.00	0.35
RI	0.01	0.01	0.01	0.00	0.00	0.03
SC	1.01	0.30	-0.30	-0.12	0.00	0.89
SD	10.91	4.50	-1.82	-0.47	0.00	13.11
TN	2.31	1.22	-1.08	-0.52	0.00	1.93
TX	10.86	13.96	1.70	1.39	2.93	30.85
UT	0.72	1.19	0.06	0.13	0.00	2.09
VT	0.30	0.10	-0.06	-0.06	0.00	0.28
VA	1.19	0.89	-0.94	-0.39	0.00	0.75
WA	3.15	1.08	0.06	0.19	0.00	4.48
WV	0.22	0.36	-0.15	-0.27	0.00	0.15
WI	6.55	1.32	1.45	-0.11	0.00	9.21
WY	1.32	3.71	-0.25	1.35	0.00	6.14

^a N₂O emissions are not reported for Alaska and Hawaii except from managed and unmanaged manure and biosolids applications, which are estimated with the Tier 1 method.

Note: NE means that emissions are not estimated for the state.

Tier 3 Model Description, Parameterization and Evaluation

The DayCent ecosystem model (Parton et al. 1998; Del Grosso et al. 2001, 2011) simulates biogeochemical carbon and nitrogen fluxes between the atmosphere, vegetation, and soil. The model is consistent with the approaches laid out in the *2006 IPCC Guidelines* but provides a more complete estimation of soil N₂O emissions than IPCC Tier 1 or 2 methods by accounting for a broader suite of environmental drivers that influence emissions and carbon stock changes. These drivers include soil characteristics, weather patterns, crop and forage characteristics, and management practices. The DayCent model utilizes the soil carbon modeling framework developed in the Century model (Parton et al. 1987, 1988, 1994; Metherell et al. 1993), but has been refined to simulate dynamics at a daily time-step. Carbon and nitrogen dynamics are linked in plant-soil systems through biogeochemical processes of microbial decomposition and plant production (McGill and Cole 1981). Coupling the three source categories (i.e., agricultural soil organic carbon, rice CH₄ and soil N₂O) in a single inventory analysis ensures that there is a consistent treatment of the processes and interactions between carbon and nitrogen cycling in soils, and ensuring conservation of mass. For example, plant growth is controlled by nutrient availability, water, and temperature stress. Plant growth, along with residue management, determines carbon inputs to soils and influences carbon stock changes. Removal of soil mineral nitrogen by microbial organisms influences the amount of production and carbon inputs, while plant uptake of nitrogen influences availability of nitrogen for microbial processes of nitrification and denitrification that generate N₂O emissions. Nutrient supply is a function of external nutrient additions as well as litter and soil organic matter (SOM) decomposition rates, and increasing decomposition can lead to a reduction in soil organic carbon stocks due to microbial decomposition, and greater N₂O emissions by enhancing mineral nitrogen availability in soils.

The DayCent process-based simulation model (daily time-step version of the Century model) has been selected for the Tier 3 approach based on the following criteria:

- 1) The model has been developed in the United States and extensively tested for U.S. conditions (e.g., Parton et al. 1987, 1993). In addition, the model has been widely used by researchers and agencies in many other parts of the world for simulating soil carbon dynamics at local, regional and national scales (e.g., Brazil, Canada, India, Jordan, Kenya, Mexico), soil N₂O emissions (e.g., Canada, China, Ireland, New Zealand) (Abdalla et al. 2010; Li et al. 2005; Smith et al. 2008; Stehfest and Muller 2004; Cheng et al. 2014), and CH₄ emissions (Cheng et al. 2013).
- 2) The model is designed to simulate management practices that influence soil carbon dynamics, CH₄ emissions and direct N₂O emissions, with the exception of cultivated organic soils; cobbly, gravelly, or shaley soils; and crops that have not been parameterized for DayCent simulations (e.g., some vegetables, perennial/horticultural crops, and crops that are rotated with these crops). For these latter cases, an IPCC Tier 2 method has been used to estimate soil organic carbon stock changes, and an IPCC Tier 1 method is used to estimate CH₄ and N₂O emissions. The model can also be used to estimate the amount of nitrate leaching and runoff, as well as volatilization of ammonia and nitrogen oxides, which are subject to indirect N₂O emissions.
- 3) Much of the data needed for the model is available from existing national databases. The exceptions are management of federal grasslands and amendments of biosolids (i.e., treated sewage sludge) to soils, which are not known at a sufficient resolution or detail to use the Tier 3 model. Soil N₂O emissions and carbon stock changes associated with these practices are addressed with Tier 1 and 2 methods, respectively.

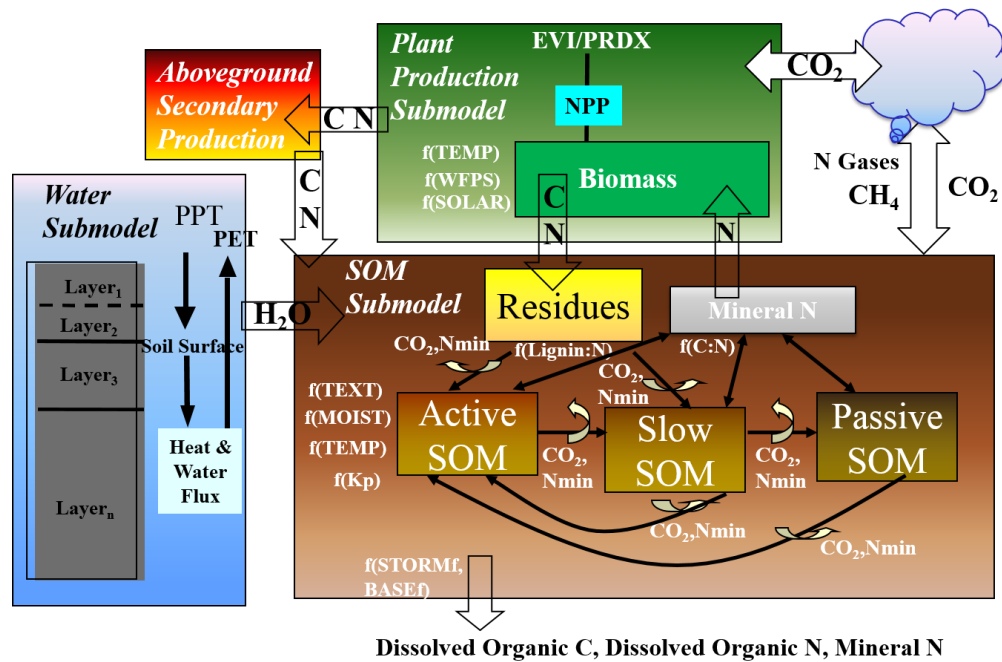
DayCent Model Description

Key processes simulated by DayCent include (1) plant growth; (2) organic matter formation and decomposition; (3) soil water and temperature regimes by layer; (4) nitrification and denitrification processes; and (5) methanogenesis (Figure A-10). Each submodel is described below.

- 1) The plant-growth submodel simulates carbon assimilation through photosynthesis; nitrogen uptake; dry matter production; partitioning of carbon within the crop or forage; senescence; and mortality. The primary function of the growth submodel is to estimate the amount, type, and timing of organic matter inputs to soil, and to represent the influence of the plant on soil water, temperature, and N balance. Yield and removal of harvested biomass are also simulated. Separate submodels are designed to simulate herbaceous plants (i.e., agricultural crops and grasses) and woody vegetation (i.e., trees and scrub). Maximum daily net primary production (NPP) is estimated using the NASA-

CASA production algorithm (Potter et al.1993, 2007) and MODIS Enhanced Vegetation Index (EVI) products, MOD13Q1 and MYD13Q1. The NASA-CASA production algorithm is only used for the following major crops: corn, soybeans, sorghum, cotton, wheat, and other close-grown crops such as barley and oats.¹¹¹ Model evaluation has shown that the NASA-CASA algorithm improves the precision of NPP estimates by using the EVI products to inform the production model. The r^2 is 83 percent for the NASA-CASA algorithm and 64 percent for the single parameter value approach. See Figure A-11. Other regions and crops are simulated with a single value for the maximum daily NPP, instead of the more dynamic NASA-CASA algorithm. The maximum daily NPP rate is modified by air temperature and available water to capture temperature and moisture stress, and then production is further subject to nutrient limitations (i.e., nitrogen).

Figure A-10: DayCent Model Flow Diagram

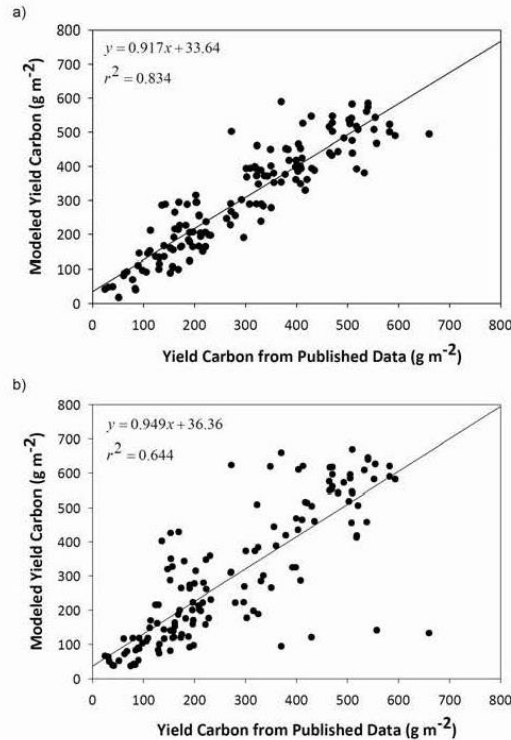


- 2) Dynamics of soil organic carbon and nitrogen (Figure A-10) are simulated for the surface and belowground litter pools and soil organic matter in the top 30 cm of the soil profile; mineral nitrogen dynamics are simulated through the whole soil profile. Organic carbon and nitrogen stocks are represented by two plant litter pools (metabolic and structural) and three soil organic matter (SOM) pools (active, slow, and passive). The metabolic litter pool represents the easily decomposable constituents of plant residues, while the structural litter pool is composed of more recalcitrant, ligno-cellulose plant materials. The three SOM pools represent a gradient in decomposability, from active SOM (representing microbial biomass and associated metabolites) having a rapid turnover (months to years), to passive SOM (representing highly processed, humified, condensed decomposition products), which is highly recalcitrant, with mean residence times on the order of several hundred years. The slow pool represents decomposition products of intermediate stability, having a mean residence time on the order of decades and is the fraction that tends to be influenced the most by land use and management activity. Soil texture influences turnover rates of the slow and passive pools. The clay and silt-sized mineral fraction of the soil provides physical protection from microbial decomposition, leading to enhanced SOM stabilization in finely textured soils. Soil temperature and moisture, tillage disturbance, aeration, and other factors influence decomposition and loss of carbon from the soil organic matter pools.

¹¹¹ It is a planned improvement to estimate NPP for additional crops and grass forage with the NASA-CASA method in the future.

- The soil-water module simulates water flows and changes in soil water availability, which influences both plant growth, decomposition and nutrient cycling. Soil moisture content is simulated through a multi-layer profile based on precipitation, snow accumulation and melting, interception, soil and canopy evaporation, transpiration, soil water movement, runoff, and drainage.

Figure A-11: Modeled versus measured net primary production



Part a) presents results of the NASA-CASA algorithm ($r^2 = 83\%$) and part b) presents the results of a single parameter value for maximum net primary production ($r^2 = 64\%$).

- Soil mineral nitrogen dynamics are modeled based on nitrogen inputs from fertilizer inputs (synthetic and organic), residue nitrogen inputs, soil organic matter mineralization in addition to symbiotic and asymbiotic nitrogen fixation. Mineral nitrogen is available for plant and microbial uptake and is largely controlled by the specified stoichiometric limits for these organisms (i.e., C:N ratios). Mineral and organic nitrogen losses are simulated with leaching and runoff, and nitrogen can be volatilized and lost from the soil through ammonia volatilization, nitrification and denitrification. Soil N_2O emissions occur through nitrification and denitrification. Denitrification is a function of soil NO_3^- concentration, water filled pore space (WFPS), heterotrophic (i.e., microbial) respiration, and texture. Nitrification is controlled by soil ammonium (NH_4^+) concentration, water filled pore space, temperature, and pH (See Box A-2 for more information).
- Methanogenesis is modeled under anaerobic conditions and is controlled by carbon substrate availability, temperature, and redox potential (Cheng et al. 2013). Carbon substrate supply is determined by decomposition of residues and soil organic matter, in addition to root exudation. The transport of CH_4 to the atmosphere occurs through the rice plant and via ebullition (i.e., bubbles). CH_4 can be oxidized (methanotrophy) as it moves through a flooded soil and the oxidation rates are higher as the plants mature and in soils with more clay (Sass et al. 1994).

The model allows for a variety of management options to be simulated, including different crop types, crop sequences (e.g., rotation), cover crops, tillage practices, fertilization, organic matter addition (e.g., manure amendments), harvest events (with variable residue removal), drainage, flooding, irrigation, burning, and grazing intensity. An input “schedule” file is used to simulate the timing of management activities and temporal trends; schedules can be organized into discrete time blocks to define a repeated sequence of events (e.g., a crop rotation or a frequency of disturbance such as

a burning cycle for perennial grassland). Management options can be specified for any day of a year within a scheduling block, where management codes point to operation-specific parameter files (referred to as *.100 files), which contain the information used to simulate management effects. User-specified management activities can be defined by adding to or editing the contents of the *.100 files. Additional details of the model formulation are given in Parton et al. (1987, 1988, 1994, 1998), Del Grosso et al. (2001, 2011), Cheng et al. (2013) and Metherell et al. (1993), and archived copies of the model source code are available.

Box A-2: DayCent Model Simulation of Nitrogen Gas losses and Nitrate Leaching

The DayCent model simulates the two biogeochemical processes, nitrification and denitrification, that result in N₂O and NO_x emissions from soils (Del Grosso et al. 2000, Parton et al. 2001). Nitrification is calculated for the top 15 cm of soil (where nitrification mostly occurs) while denitrification is calculated for the entire soil profile (accounting for denitrification near the surface and subsurface as nitrate leaches through the profile). The equations and key parameters controlling N₂O emissions from nitrification and denitrification are described below.

Nitrification is controlled by soil ammonium (NH₄⁺) concentration, temperature (t), Water Filled Pore Space (WFPS) and pH according to the following equation:

Equation A-42: Soil Nitrification Rate

$$\text{Nit} = \text{NH}_4^+ \times K_{\text{max}} \times F(t) \times F(\text{WFPS}) \times F(\text{pH})$$

where,

Nit	=	the soil nitrification rate (g N/m ² /day)
NH ₄ ⁺	=	the model-derived soil ammonium concentration (g N/m ²)
K _{max}	=	the maximum fraction of NH ₄ ⁺ nitrified (K _{max} = 0.10/day)
F(t)	=	the effect of soil temperature on nitrification (Figure A-12a)
F(WFPS)	=	the effect of soil water content and soil texture on nitrification (Figure A-12b)
F(pH)	=	the effect of soil pH on nitrification (Figure A-12c)

The current parameterization used in the model assumes that 1.2 percent of nitrified nitrogen is converted to N₂O.

The model assumes that denitrification rates are controlled by the availability of soil NO₃⁻ (electron acceptor), labile carbon compounds (electron donor) and oxygen (competing electron acceptor). Heterotrophic soil respiration is used as a proxy for labile carbon availability, while oxygen availability is a function of soil physical properties that influence gas diffusivity, soil WFPS, and oxygen demand. The model selects the minimum of the NO₃⁻ and CO₂ functions to establish a maximum potential denitrification rate. These rates vary for particular levels of electron acceptor and carbon substrate, and account for limitations of oxygen availability to estimate daily denitrification rates according to the following equation:

Equation A-43: Soil Denitrification Rate

$$\text{Den} = \min[F(\text{CO}_2), F(\text{NO}_3)] \times F(\text{WFPS})$$

where,

Den	=	the soil denitrification rate (µg N/g soil/day)
F(NO ₃)	=	a function relating N gas flux to nitrate levels Figure A-13a)
F(CO ₂)	=	a function relating N gas flux to soil respiration (Figure A-13b)
F(WFPS)	=	a dimensionless multiplier (Figure A-13c)

The x inflection point of F(WFPS) is a function of respiration and soil gas diffusivity at field capacity (D_{FC}):

Equation A-44: Inflection Point Calculation

$$x \text{ inflection} = 0.90 - M(\text{CO}_2)$$

where,

M	=	a multiplier that is a function of D _{FC} . In technical terms, the inflection point is the domain where either F(WFPS) is not differentiable or its derivative is 0. In this case, the inflection
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point can be interpreted as the WFPS value at which denitrification reaches half of its maximum rate.

Respiration has a much stronger effect on the water curve in clay soils with low D_{FC} than in loam or sandy soils with high D_{FC} (Figure A-12). The model assumes that microsites in fine-textured soils can become anaerobic at relatively low water contents when oxygen demand is high. After calculating total nitrogen gas flux, the ratio of N_2/N_2O is estimated so that total nitrogen gas emissions can be partitioned between N_2O and N_2 :

Equation A-45: Ratio of Nitrogen Gas (N_2) to Nitrous Oxide

$$R_{N_2/N_2O} = F_r(NO_3/CO_2) \times F_r(WFPS).$$

where,

R_{N_2/N_2O}	=	the ratio of N_2/N_2O
$F_r(NO_3/CO_2)$	=	a function estimating the impact of the availability of electron donor relative to substrate
$F_r(WFPS)$	=	a multiplier to account for the effect of soil water on $N_2:N_2O$.

For $F_r(NO_3/CO_2)$, as the ratio of electron donor to substrate increases, a higher portion of nitrogen gas is assumed to be in the form of N_2O . For $F_r(WFPS)$, as WFPS increases, a higher portion of nitrogen gas is assumed to be in the form of N_2 .

After calculating and summing N_2O emissions from nitrification and denitrification, NO_x emissions are calculated using a NO_x/N_2O ratio function based on soil gas diffusivity. The NO_x/N_2O ratio is high (maximum of about 17) when soil gas diffusivity is high and decreases to a minimum of approximately 0.28 as diffusivity decreases.

Ammonia volatilization is simulated less mechanistically than the other nitrogen gas losses. A soil texture specific portion of nitrogen excreted from animals ranging from 15-30 percent is assumed to be volatilized with more volatilization as soil texture becomes coarser. In addition, a plant specific portion ranging from 2-15 percent of harvested or senesced biomass nitrogen is assumed to be volatilized.

A portion of the nitrate is assumed to be dissolved and flows with water between soil layers during saturated and unsaturated water movement. The portion of nitrate that flows from the upper layer to the lower layer increases with increasing sand content and with water flow volume so most movement occurs during saturated flow events triggered by precipitation or irrigation. The amount of nitrate leaching for estimating indirect N_2O emissions is based on the nitrate that flows through the entire profile in the model simulation. In addition to sand content, leaching rates are influenced by soil depth, plant nitrogen demand, precipitation event size, and other factors.

Figure A-12: Effect of Soil Temperature (a), Water-Filled Pore Space (b), and pH (c) on Nitrification Rates

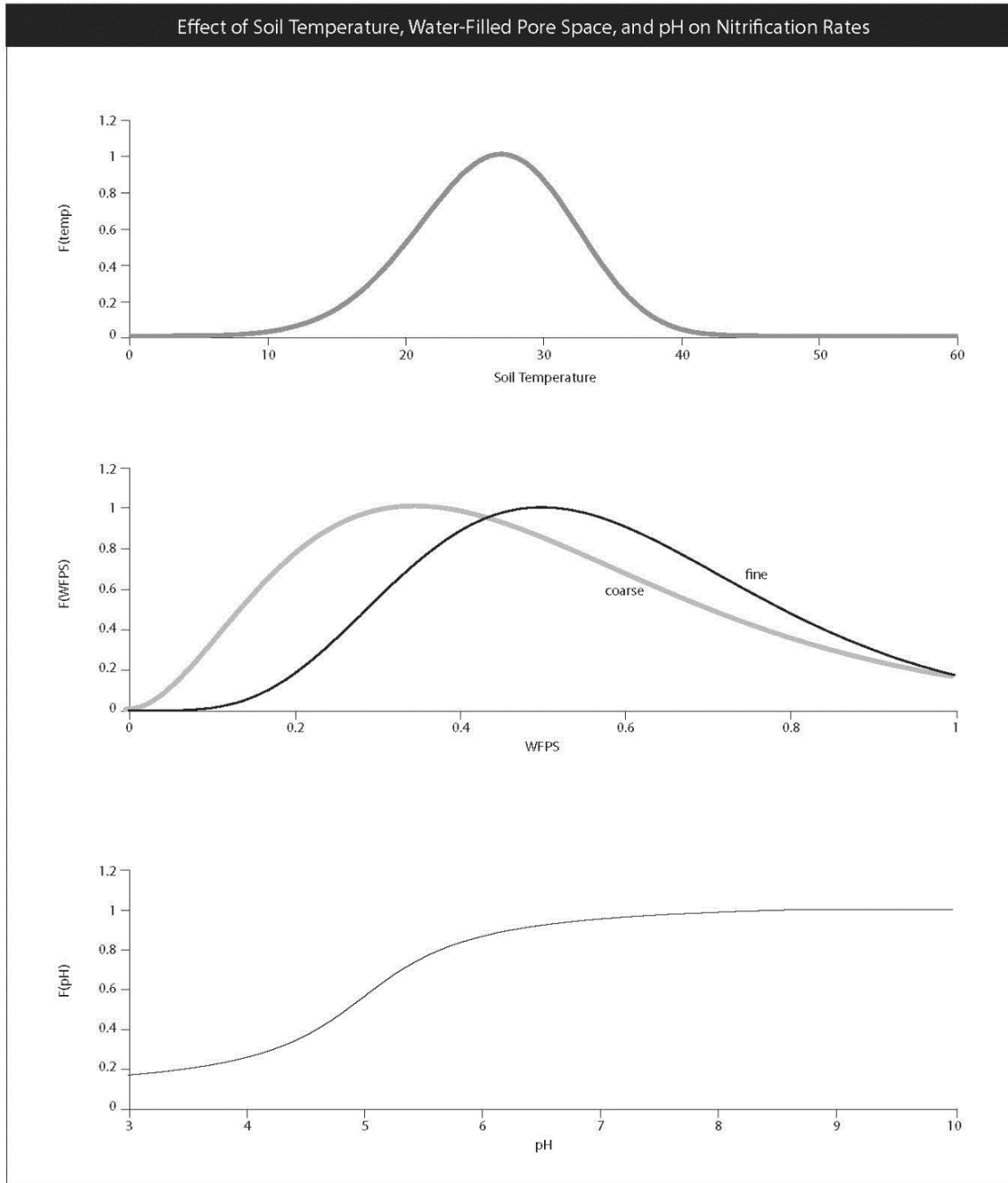
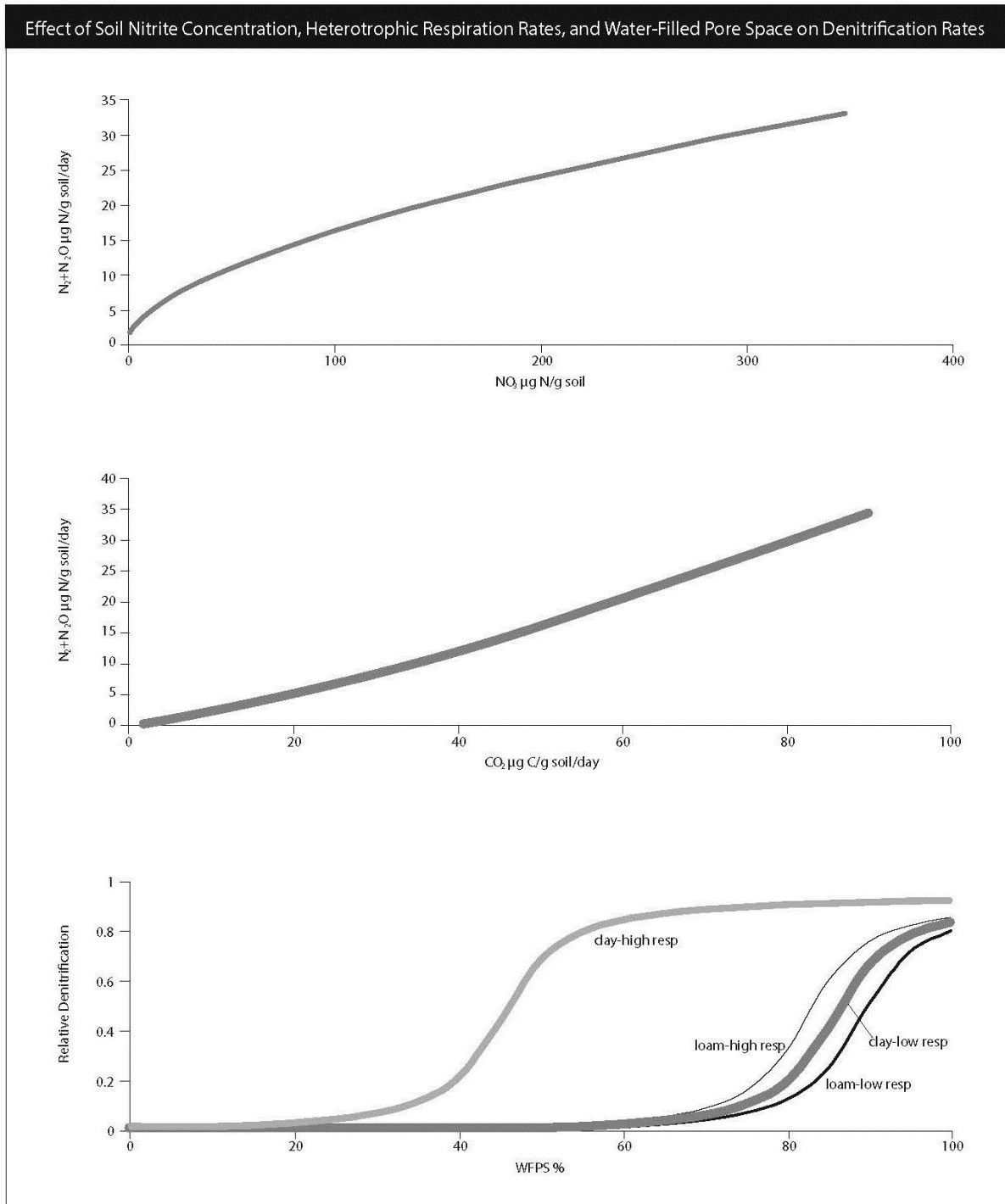


Figure A-13: Effect of Soil Nitrite Concentration (a), Heterotrophic Respiration Rates (b), and Water-Filled Pore Space (c) on Denitrification Rates



Pulses of N_2O emissions can occur during freeze-thaw events in soils of cold climates, and these events can contribute a substantial portion of annual emissions in northern temperate and boreal regions (Butterbach-Bahl et al. 2017; Wagner-Riddle et al. 2017; Del Grosso et al. 2022). The mechanisms responsible for this phenomenon are not entirely understood but the general hypotheses include accumulation of substrates while the soil is frozen that drives denitrification as the soil thaws; impacts on soil gas diffusivity and O_2 availability in pores during freeze-thaw events that influence denitrification rates; and differing temperature sensitivities of the enzymatic processes that control the amounts of N_2 and

N₂O gases released during denitrification (Congreves et al. 2018). The denitrification routine in DayCent was amended so that periods of thawing of frozen soils in the 2-5 cm layer during the late winter/spring will trigger a pulse of N₂O emissions (Del Grosso et al. 2022). Specifically, the soil water content and microbial respiration controls on denitrification are relaxed for approximately 3 days upon melting and N₂O from denitrification is amplified by an amount proportional to cumulative freezing degree days during the winter season. DayCent was evaluated using annual high frequency N₂O data collected at research sites in eastern and western Canada (Wagner-Riddle et al. 2017) and fluxes derived from atmospheric data (Nevison et al. 2017). The results showed less bias with a better match to observed patterns of late winter/spring emissions than the previous version of the DayCent model (Del Grosso et al. 2022).

DayCent Model Parameterization

DayCent has been widely applied and calibrated over the years through manual parameterization (e.g., Parton et al. 1998; Del Grosso et al. 2001). However, manual approaches do not necessarily provide the best calibration for a process-based model, and so there is an effort underway to re-parameterize DayCent with Bayesian calibration methods. There are three steps to this calibration method: a) conduct a sensitivity analysis to identify the most influential parameters, b) conduct the Bayesian calibration with the most sensitive parameters, and 3) evaluate the results with independent data. First, the framework uses a global sensitivity analysis to evaluate the importance of parameters given their full parameter space and potential interactions with other parameters (Saltelli et al. 2008). This approach is considered more robust for ranking parameter importance rather than a local sensitivity analysis that focuses on the effect of varying one parameter, generally within a small area of the overall parameter space. The Sobol method is used to conduct the global sensitivity analysis (Sobol 2001), which is appropriate for the complexity in the DayCent model (Saltelli 2002). Second, the model is calibrated using Bayesian logic with the Sampling Importance Resampling (SIR) method (Rubin 1987, Rubin 1988). A set of prior parameter distributions are developed based on the knowledge of the inventory compilers and information in the published literature. The model is then applied in a Monte Carlo analysis by randomly selecting values from the prior parameter distributions using a Latin Hypercube Sampling (LHS) approach. The LHS approach for selecting parameters allows for values that are used in the simulations to be distributed throughout the entire domain of the prior parameter distributions. The posterior distribution is approximated from the results generated by the Monte Carlo analysis using a likelihood function and weighting parameters based on the level of mismatch between modeled and measured emissions or soil organic carbon stock changes. If the data are informative, the likelihood will update the prior parameter distribution based on the weighting and lead to more resolved joint posterior parameter distribution. Third, the model is applied to simulate experimental sites that are not used in the Bayesian calibration, and the results are evaluated relative to the model application with the prior parameter distributions. If the model has been improved through the calibration process, then the results should have less bias and/or variance than the model application with the prior parameter distributions.

This Bayesian calibration model framework has initially been applied to calibrate DayCent for modeling soil organic carbon stock changes to a 30 cm depth (Gurung et al. 2020). The analysis reduced uncertainty in model predictions by a factor of 6.6. See Gurung et al. (2020) for more detail about this application. We anticipate expanding the calibration to other model processes in the near future, and eventually using the joint posterior parameter distribution to quantify uncertainty in model predictions. In this *Inventory*, the *maximum a posterior* value for each parameter from the posterior distribution has been used to simulate soil organic carbon stock changes.

DayCent Model Evaluation

DayCent has been applied to sites that are independent from model calibration to evaluate the model for estimating greenhouse gas emissions in the United States inventory. Moreover, these analyses are used to quantify uncertainty with an empirical approach as discussed in Step 2a of this annex (Ogle et al. 2007). The model was tested and shown to capture the general trends in carbon storage across 1406 observations from 69 long-term experiment sites and 145 NRI soil monitoring network sites (Spencer et al. 2011) (Figure A-14). Some bias and imprecision occur in predictions of soil organic carbon, which is reflected in the uncertainty associated with DayCent model results. Regardless, the Tier 3 approach has considerably less uncertainty than Tier 1 and 2 methods (Del Grosso et al. 2010; Figure A-15).

Figure A-14: Comparisons of Results from DayCent Model and Measurements of Soil Organic Carbon Stocks

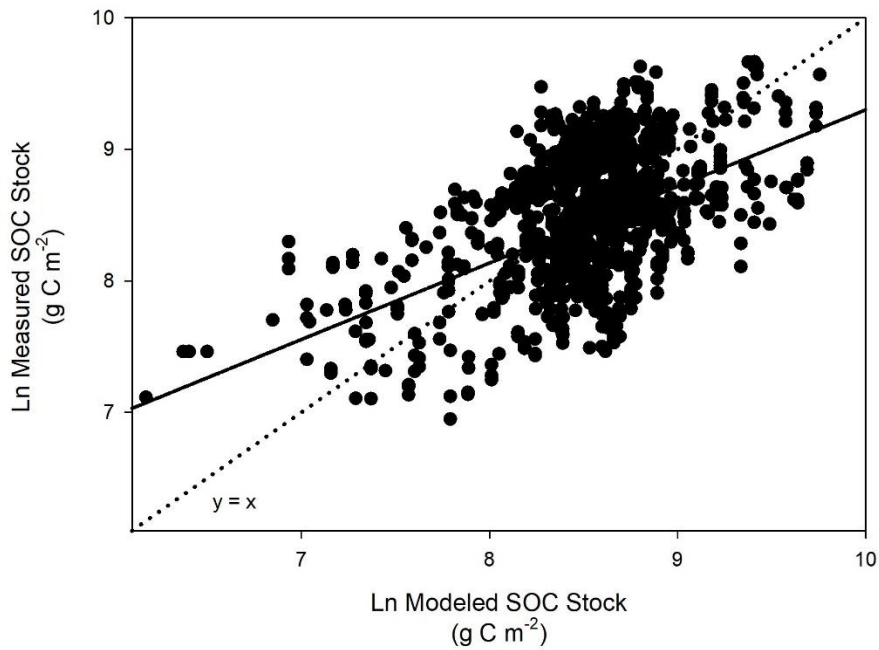
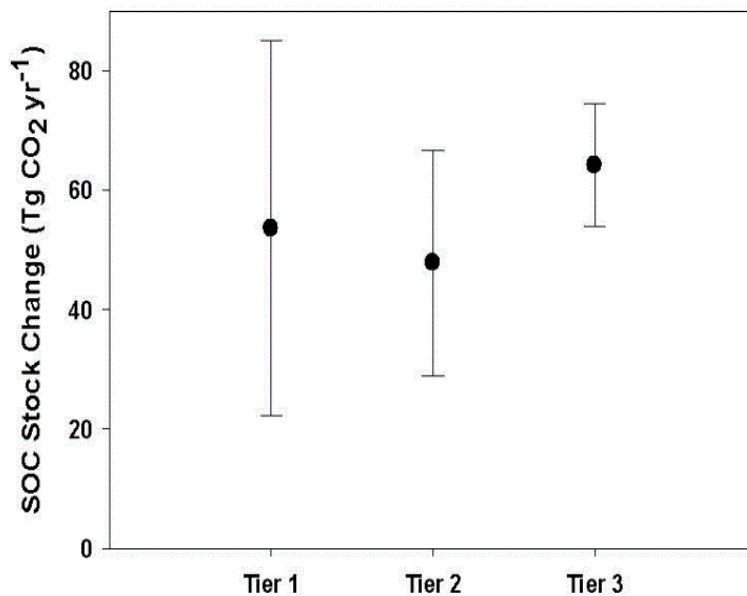


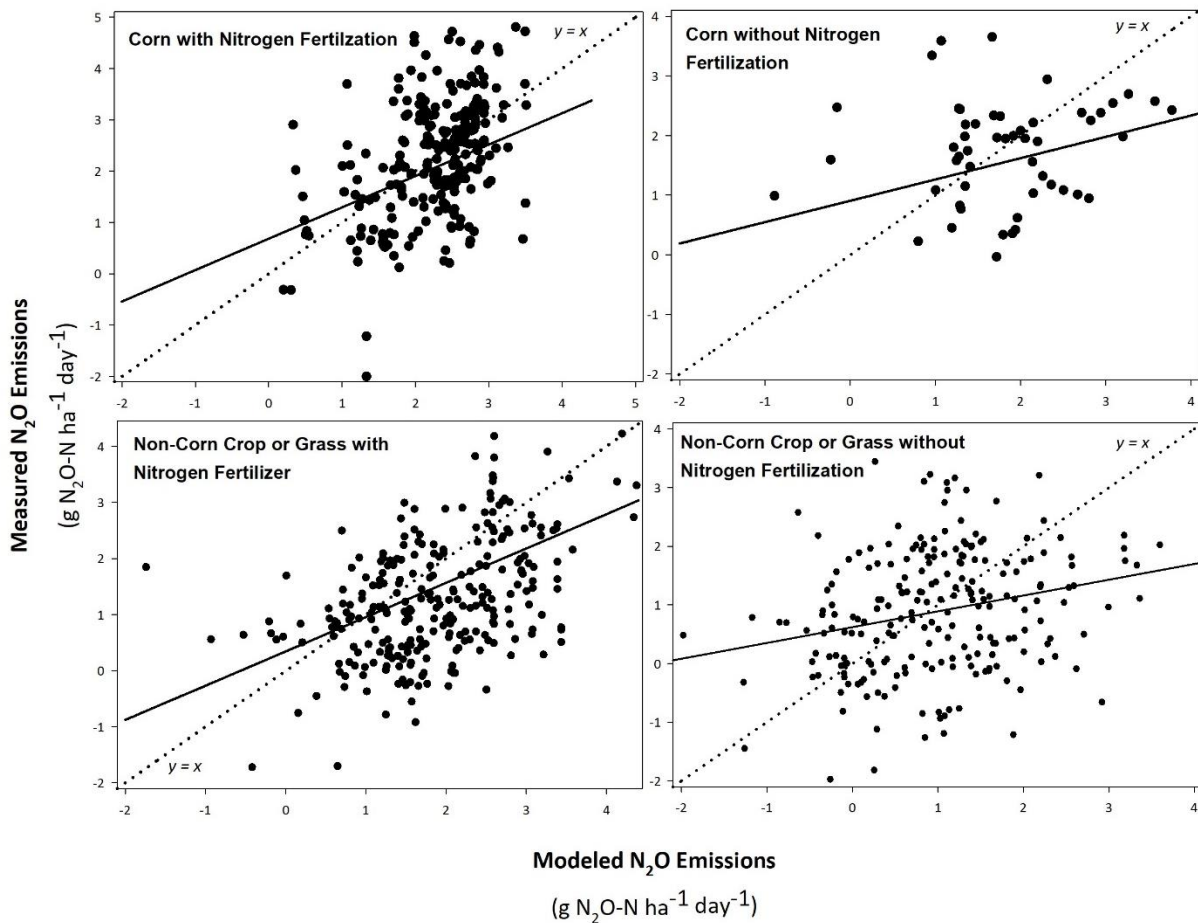
Figure A-15: Comparison of Estimated Soil Organic Carbon Stock Changes and Uncertainties using Tier 1 (IPCC 2006), Tier 2 (Ogle et al. 2003, 2006) and Tier 3 Methods



DayCent model results have also been compared to trace gas N₂O fluxes for native and managed systems including 76 experimental sites with about 857 observations (Figure A-15). In general, the model simulates reasonable patterns for the emissions, but there are some biases and imprecision in the predictions, which is reflected in the uncertainty associated with DayCent model results. Comparisons with measured data showed that DayCent estimated N₂O emissions more accurately and precisely than the IPCC Tier 1 methodology (IPCC 2006) with higher r² values and a fitted line closer

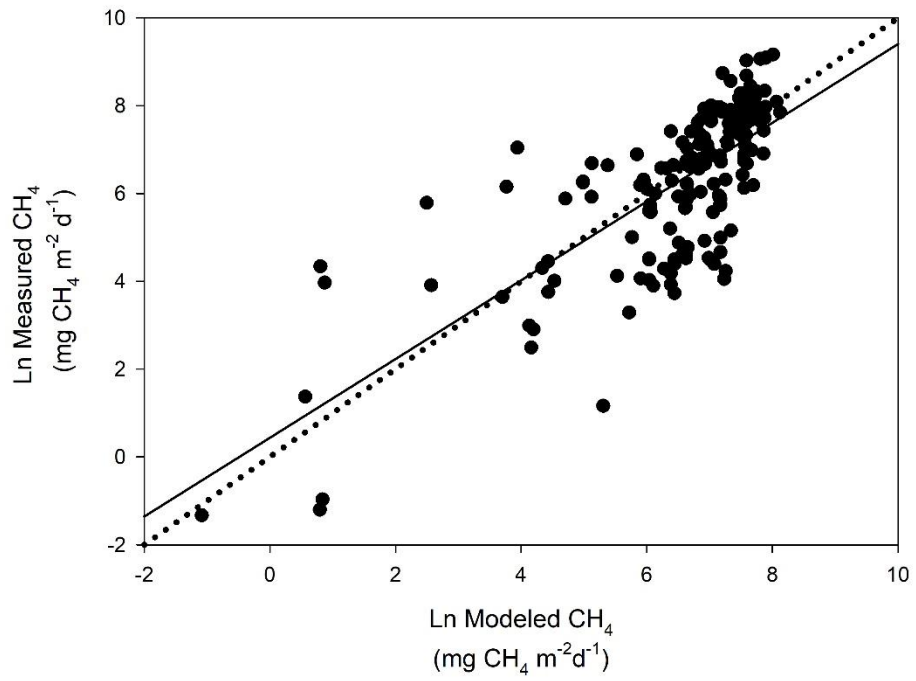
to a perfect 1:1 relationship between measured and modeled N_2O emissions (Del Grosso et al. 2005, 2008b). This is not surprising, since DayCent includes site-specific factors (climate, soil properties, and previous management) that influence N_2O emissions. Furthermore, DayCent also simulated NO_3^- leaching (root mean square error = 20 percent) more accurately than IPCC Tier 1 methodology (root mean square error = 69 percent) (Del Grosso et al. 2005). Volatilization of N gases that contribute to indirect soil N_2O emissions is the only component that has not been thoroughly tested, which is due to a lack of measurement data.

Figure A-16: Comparisons of Results from the DayCent Model and Measurements of Soil Nitrous Oxide Emissions



DayCent predictions of soil CH_4 emissions have also been compared to experimental measurements from sites in California, Texas, Arkansas, and Louisiana (Figure A-17). There are 17 long-term experiments with data on CH_4 emissions from rice cultivation, representing 238 treatment observations. In general, the model estimates CH_4 emissions with no apparent bias, but there is a lack of precision, which is addressed in the uncertainty analysis.

Figure A-17: Comparisons of Results from DayCent Model and Measurements of Soil Methane Emissions from Rice Cultivation



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3.13. Methodology for Estimating Net Carbon Stock Changes in Forest Ecosystems and Harvested Wood Products for Forest Land Remaining Forest Land and Land Converted to Forest Land as well as Non-CO₂ Emissions from Forest Fires

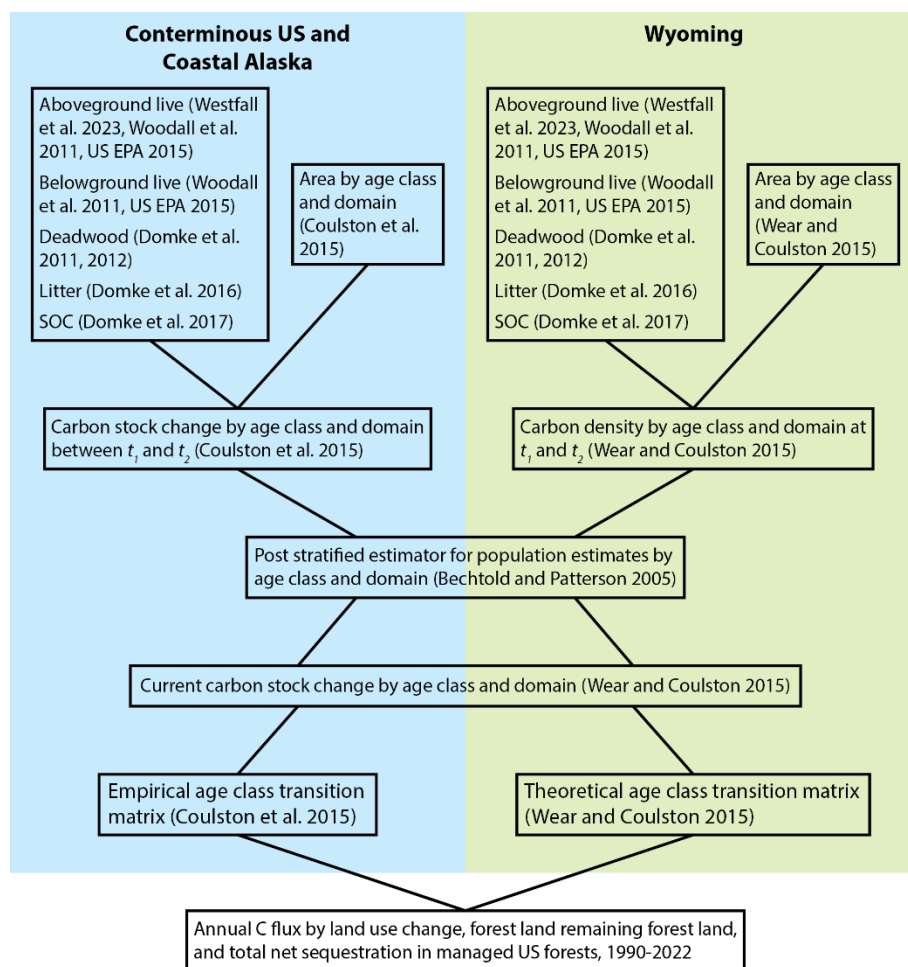
This annex expands on the methodology used to estimate net changes in carbon (C) stocks in forest ecosystems and harvested wood products for forest land remaining forest land and land converted to forest land as well as non-CO₂ emissions from forest fires. Full details of the carbon conversion factors and procedures may be found in the cited references. For details on the methods used to estimate changes in mineral soil carbon stocks in the land converted to forest land section please refer to Annex 3.12.

Carbon stocks and net stock change in forest ecosystems

The inventory-based methodologies for estimating forest carbon stocks are based on a combination of approaches (Woodall et al 2015a) and are consistent with the IPCC (2003, 2006) stock-difference (used for the conterminous United States and coastal southeast and southcentral Alaska) and gain-loss (used for interior Alaska, Hawaii, and the U.S. Territories) methods. Estimates of ecosystem carbon are based on data from the network of periodic and annual national forest inventory (NFI) plots established and measured by the Forest *Inventory and Analysis* (FIA) program within the USDA Forest Service; either direct measurements or variables from the NFI are the basis for estimating metric tons of carbon per hectare in forest ecosystem carbon pools (i.e., above- and belowground biomass, dead wood, litter, and soil organic carbon (SOC)). For the conterminous United States and coastal Alaska, plot-level estimates are used to inform land area (by use) and stand age transition matrices across time which can be summed annually for an estimate of forest carbon stock change for forest land remaining forest land and land converted to forest land. A general description of the land use and stand age transition matrices that are informed by the annual NFI of the United States and were used in the estimation framework to compile estimates for the conterminous United States and coastal Alaska in this *Inventory* are described in Coulston et al. (2015). The annual NFI data in the conterminous United States and coastal Alaska allows for empirical estimation of the net change in forest ecosystem carbon stocks within the estimation framework. In contrast, Wyoming has a lack of remeasurement data within the NFI, so theoretical age transition matrices were developed (Figure A-18). The incorporation of all managed forest land in Alaska was facilitated by an analysis to determine the managed land base in Alaska (Ogle et al. 2018), the expansion of the NFI into interior Alaska beginning in 2014, and a myriad of publicly available data products that provided information necessary for prediction of carbon stocks and fluxes on plots that have yet to be measured as part of the NFI.

The following sections of this annex describe the estimation system used this year (Figure A-18), including the methods for estimating individual pools of forest ecosystem carbon in addition to the approaches used to inform land use and stand age transitions.

Figure A-18: Flowchart of the inputs necessary in the estimation framework, including the methods for estimating individual pools of forest carbon in the conterminous United States and Coastal Alaska



Note: An empirical age class transition matrix was used in Coastal Alaska and every state in the conterminous United States with the exception of Wyoming where a theoretical age class transition matrix was used due to a lack of remeasurements in the annual NFI.

Forest Land Definition

The definition of forest land within the United States and used for this *Inventory* is defined in Oswald et al. (2019) as “Land at least 120 feet (37 meters) wide and at least 1 acre (0.4 hectare) in size with at least 10 percent cover (or equivalent stocking) by live trees including land that formerly had such tree cover and that will be naturally or artificially regenerated. Trees are woody plants having a more or less erect perennial stem(s) capable of achieving at least 3 inches (7.6 cm) in diameter at breast height (dbh), or 5 inches (12.7 cm) diameter at root collar, and a height of 16.4 feet (5 meters) at maturity in situ. The definition here includes all areas recently having such conditions and currently regenerating or capable of attaining such condition in the near future. Forest land also includes transition zones, such as areas between forest and non-forest lands that have at least 10 percent cover (or equivalent stocking) with live trees and forest areas adjacent to urban and built-up lands. Unimproved roads and trails, streams, and clearings in forest areas are classified as forest if they are less than 120 feet (36.6 meters) wide or an acre (0.4 hectare) in size. Forest land does not include land that is predominantly under agricultural or urban land use.” Timberland is productive forest land, which is on unreserved land and is producing or capable of producing crops of industrial wood. This is an important subclass of forest land because timberland is the primary source of carbon incorporated into harvested wood products. Productivity

for timberland is at a minimum rate of 20 cubic feet per acre (1.4 cubic meters per hectare) per year of industrial wood (Woudenberg and Farrenkopf 1995). There are about 208 million hectares of timberland in the conterminous United States, which represents 67 percent of all forest lands over the same area (Oswalt et al. 2019).

Forest Inventory Data

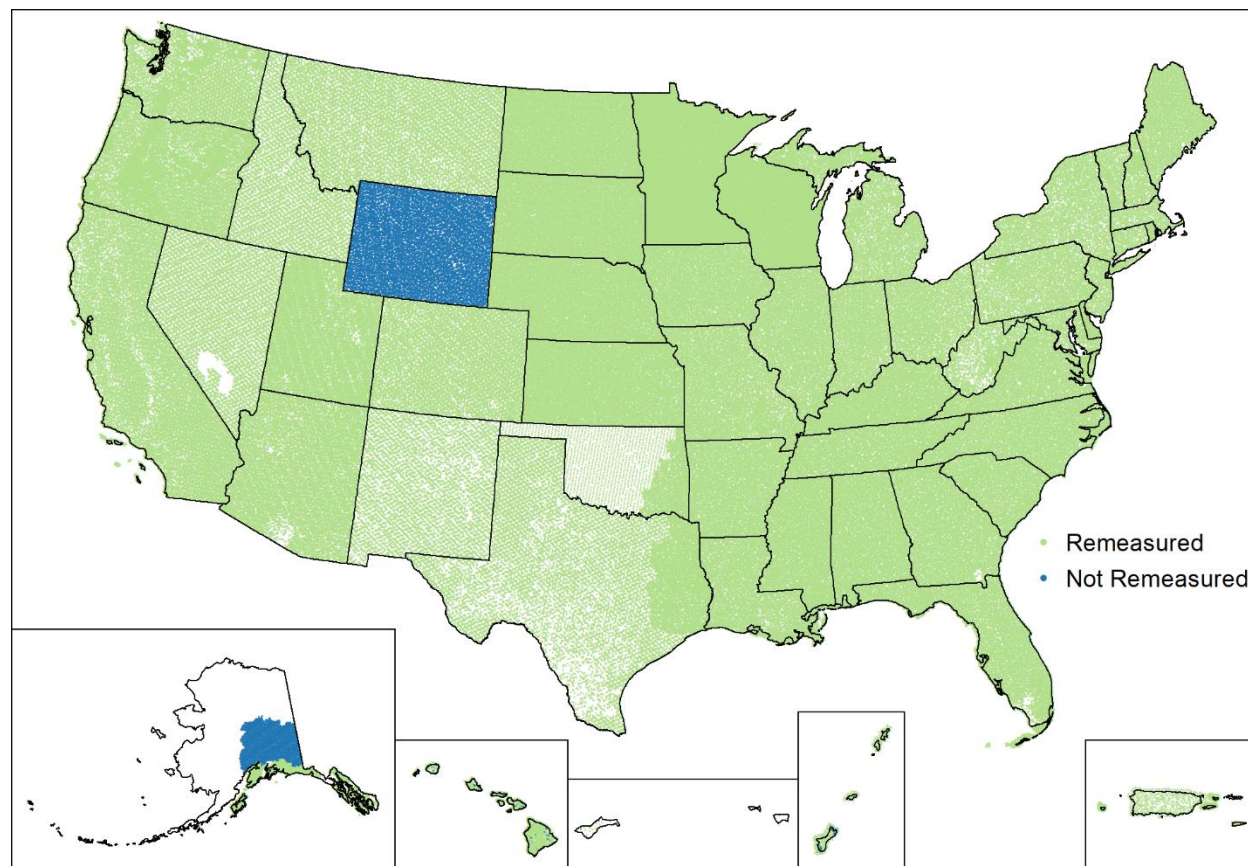
The estimates of forest carbon stocks are based on data from the annual NFI. NFI data were obtained from the USDA Forest Service FIA Program (Frayer and Furnival 1999; USDA Forest Service 2023a; USDA Forest Service 2023b). NFI data include remote sensing information and a collection of field measurements at sample locations called plots. Tree measurements include diameter at breast height (dbh), tree height, species, and variables describing tree form and condition. On a subset of plots, additional measurements or samples are taken on downed dead wood, litter, and soil variables. The technical advances needed to estimate carbon stocks from these data are ongoing (Woodall et al. 2015a) with the latest research incorporated on an annual basis (see Domke et al. 2022, Westfall et al. 2023). The field protocols are thoroughly documented and available for download from the USDA Forest Service (2023c). Bechtold and Patterson (2005) provide the estimation procedures for NFI population estimation. The data are freely available for download at USDA Forest Service (2011b) as the FIA Database (FIADB) Version 8.0 (USDA Forest Service 2023b; USDA Forest Service 2023c); these are the primary sources of NFI data used to estimate forest carbon stocks. In addition to the field sampling component, fine-scale remotely sensed imagery (National Agriculture Imagery Program) (NAIP 2015; Woodall et al. 2015b) is used to assign the land use at each sample location which has a nominal spatial resolution (raster cell size) of 1 m². Prior to field measurement of each year's collection of annual plots due for measurement (i.e., panel), each sample location in the panel (i.e., systematic distribution of plots within each state each year) is photo-interpreted manually to classify the land use. Annual NFI data are available for the temperate oceanic ecoregion of Alaska (southeast and south central) from 2004 to present as well as for interior Alaska from a pilot inventory in 2014 which became operational in 2016. Agroforestry systems are not currently accounted for in this *Inventory*, since they are not explicitly inventoried by either of the two primary national natural resource inventory programs: the FIA program of the USDA Forest Service and the National Resources *Inventory* (NRI) of the USDA Natural Resources Conservation Service (Perry et al. 2005). The majority of these tree-based practices do not meet the size and definitions for forests within each of these resource inventories.

A national plot design and annualized sampling (USDA Forest Service 2023a) were introduced by FIA with most new annual NFIs beginning after 1998. These annual NFIs are used in combination with periodic NFIs for most of the U.S. Territories in the compilation of estimates for this *Inventory*. The annual NFIs involve the sampling of all forest land including reserved and lower productivity lands. All conterminous states in the U.S., coastal Alaska, and most of Puerto Rico and the U.S. Virgin Islands have annualized NFI data available with substantial remeasurement (with the exception of Wyoming; Figure A-19. Annualized sampling means that a spatially representative portion of plots throughout the state are sampled each year, with the goal of measuring all plots once every 5 to 10 years, depending on the region of the U.S. The full unique set of data with all measured plots, such that each plot has been measured one time, is called a cycle. Sampling is designed such that partial inventory cycles provide usable, unbiased samples of forest inventory within the state, but with higher sampling uncertainty than the full cycle. After all plots have been measured once, the sequence continues with remeasurement of the first year's plots, starting the next new cycle. Most eastern states have completed three or four cycles of the annualized NFI (with 5–7-year remeasurements), and most western states are on their second annual cycle (with 10-year remeasurement). Annually updated estimates of forest carbon stocks are affected by the redundancy in the data used to generate the annual updates of carbon stock. For example, a typical annual inventory update for an eastern state will include new data from remeasurement on 20 percent of plots; data from the remaining 80 percent of plots is identical to that included in the previous year's annual update. The interpretation and use of the annual inventory data can affect trend estimates of carbon stocks and stock changes (e.g., estimates based on 60 percent of an inventory cycle will be different than estimates with a complete (100 percent) cycle). In general, the carbon stock and stock change estimates use annual NFI summaries (updates) with unique sets of plot-level data (that is, without redundant sets); the most-recent annual update (i.e., 2022) is the exception because it is included in stock change calculations in order to include the most recent available data for each state. The specific inventories used in this report are listed in Table A-194 and this list can be compared with the full set of summaries available for download (USDA Forest Service 2023b).

Similar methods are used in the periodic NFIs available for Hawaii (USDA Forest Service 2022a), and the Pacific Islands of American Samoa, Guam, Northern Mariana Islands (USDA Forest Service (2022b). However, in most cases, only aboveground live biomass carbon estimates are available in the periodic NFIs so IPCC (2019) defaults and country-specific estimates were used to supplement periodic NFI data. The IPCC (2019) defaults were used in this *Inventory*

where necessary because they are more contemporary than the IPCC (2006) defaults and provide more specific information for the ecological zones relevant to the Pacific Islands.

Figure A-19: Annual and Periodic FIA plots (remeasured and not remeasured) across the United States



Note: Due to the vast number of plots (where land use is measured even if no forest is present) they appear as spatially contiguous when displayed at the scale and resolution presented in this figure.

It should be noted that as the FIA program explores expansion of its vegetation inventory beyond the forest land use to other land uses (e.g., woodlands and urban areas), subsequent inventory observations will need to be delineated between forest and other land uses as opposed to a strict forest land use inventory. The forest carbon estimates provided here represent carbon stocks and stock change on managed forest lands (IPCC 2006, see Section 6.1 Representation of the U.S. Land Base), which is how all forest lands are classified. In some cases, there are NFI plots that do not meet the height component of the definition of forest land (Coulston et al. 2016). These plots are identified as “woodlands” (i.e., not forest land use) and were removed from the forest estimates and classified as grassland.¹¹² Note that minor differences (approximately 2 percent less forest land area in the conterminous United States) in identifying and classifying woodland as “forest” versus “woodland” exist between the current Resources Planning Act Assessment (RPA) data (Oswalt et al. 2019) and the FIADB (USDA Forest Service 2015b) due to a refined modelling approach developed specifically for *Inventory* reporting (Coulston et al. 2016). Plots in the coastal region of the conterminous United States were also evaluated using the National Land Cover Database (NLCD) and the Coastal Change Analysis Program data products to ensure that land areas were completely accounted for in this region and also that they were not included in both the wetlands category and the forest land category. This resulted in several NFI plots or subplots being removed from the forest land compilation.

¹¹² See the Grassland Remaining Grassland and Land Converted to Grassland sections for details.

Table A-194: Specific Annual Forest Inventories by State Used in Development of Forest Carbon Stock and Stock Change Estimate

Remeasurement States and Territories			Split Evaluation States/Territories and Periodic Inventories ¹		
State/Territory	Time 1 Year Range	Time 2 Year Range	State/Territory	Time 1 Year Range	Time 2 Year Range
Alabama	2006 - 2017	2015 - 2022	American Samoa	2001, 2012	
Alaska (Coastal)	2004 - 2008	2015 - 2019	Guam	2002, 2013	
Arizona	2001 - 2009	2011 - 2019	Hawaii	2010, 2019	
Arkansas	2012 - 2016	2017 - 2021	Northern Mariana Islands	2004, 2015	
California	2001 - 2009	2011 - 2019	Puerto Rico (Mona Island)	2008, 2013	
Colorado	2002 - 2009	2012 - 2019	Wyoming	2000	2011 - 2020
Connecticut	2009 - 2014	2015 - 2021			
Delaware	2009 - 2014	2015 - 2021			
Florida	2010 - 2016	2015 - 2019	Alaska (Interior)	2014, 2016 - 2021	
Georgia	2011 - 2018	2016 - 2021			
Idaho	2004 - 2009	2014 - 2019			
Illinois	2009 - 2014	2015 - 2021			
Indiana	2009 - 2014	2015 - 2021			
Iowa	2009 - 2014	2015 - 2021			
Kansas	2009 - 2013	2014 - 2020			
Kentucky	2005 - 2013	2013 - 2019			
Louisiana	2001 - 2012	2011 - 2019			
Maine	2012 - 2016	2017 - 2021			
Maryland	2009 - 2013	2014 - 2020			
Massachusetts	2009 - 2013	2014 - 2020			
Michigan	2009 - 2013	2014 - 2020			
Minnesota	2012 - 2016	2017 - 2021			
Mississippi	2009 - 2018	2016 - 2021			
Missouri	2009 - 2014	2015 - 2021			
Montana	2003 - 2009	2013 - 2019			
Nebraska	2009 - 2013	2014 - 2020			
Nevada	2004 - 2009	2014 - 2019			
New Hampshire	2009 - 2015	2015 - 2021			
New Jersey	2010 - 2015	2016 - 2020			
New Mexico	2005 - 2009	2015 - 2019			
New York	2009 - 2013	2014 - 2020			
North Carolina	2009 - 2019	2016 - 2022			
North Dakota	2009 - 2014	2015 - 2021			
Ohio	2009 - 2014	2015 - 2021			
Oklahoma	2009 - 2015	2016 - 2020			
Oregon	2001 - 2009	2011 - 2019			
Pennsylvania	2009 - 2014	2015 - 2021			
Puerto Rico (Mainland, Vieques, Culebra)	2011 - 2014	2016 - 2019			
Rhode Island	2009 - 2014	2015 - 2021			
South Carolina	2012 - 2016	2017 - 2021			

South Dakota	2009 - 2013	2014 - 2020
Tennessee	2005 - 2014	2013 - 2019
Texas (East)	2009 - 2018	2015 - 2021
Texas (West)	2004 - 2013	2014 - 2019
Utah	2000 - 2009	2010 - 2019
Vermont	2009 - 2014	2015 - 2021
Virginia	2012 - 2016	2017 - 2021
Washington	2002 - 2009	2012 - 2019
West Virginia	2009 - 2014	2015 - 2021
Wisconsin	2009 - 2014	2015 - 2021
U.S. Virgin Islands	2009	2014

¹ Plots in interior Alaska have not been split but are included in this column to conserve space in the table.

Note: Remeasured annual plots represent a complete inventory cycle between measurements of the same plots while split annual cycle plots represent a single inventory cycle of plots that are split where remeasurements have yet to occur.

Estimating Forest *Inventory* Plot-Level Carbon-Density

For each inventory plot in each state, field data from the FIA program are used alone or in combination with auxiliary information (e.g., climate, surficial geology, elevation) to predict carbon density for each forest ecosystem carbon pool (i.e., aboveground and belowground biomass, dead wood, litter, SOC). In the past, most of the conversion factors and models used for inventory-based forest carbon estimates (Smith et al. 2010; Heath et al. 2011) were initially developed as an extension of the forest carbon simulation model FORCARB (Heath et al. 2010). The conversion factors and model coefficients were usually categorized by region and forest type. Thus, region and type are specifically defined for each set of estimates. More recently, the coarse approaches of the past have been updated with empirical information regarding carbon variables for individual forest carbon pools such as dead wood and litter (e.g., Domke et al. 2013 and Domke et al. 2016). Factors are applied to the forest inventory data at the scale of NFI plots which are a systematic sample of all forest attributes and land uses within each state. The results are estimates of carbon density (T per hectare) for each forest ecosystem carbon pool. Carbon density for live trees, standing dead trees, understory vegetation, downed dead wood, litter, and SOC are estimated. All non-soil carbon pools except litter and downed dead wood can be separated into aboveground and belowground components. The live tree and understory carbon pools are combined into the aboveground and belowground biomass pools in this *Inventory*. Similarly, standing dead trees and downed dead wood are pooled as dead wood in this *Inventory*. Carbon stocks and fluxes for forest land remaining forest land and land converted to forest land are reported in forest ecosystem carbon pools following IPCC (2006).

Live tree carbon pools

Live tree carbon pools include aboveground and belowground (coarse root) biomass of live trees with dbh of at least 2.54 cm at 1.37 m above the forest floor. Separate estimates are made for above- and below-ground biomass components. The NSVB models have been implemented in the FIA program and associated public database (USDA Forest Service 2023b) along with a national standardization of tree defects and new carbon fractions. These new volume, biomass, and carbon estimates cover timber tree species in the conterminous United States and coastal Alaska. All other trees (i.e., trees that are woodland species and trees within Pacific and Caribbean Islands) use regional models for volume and biomass, with updated carbon fractions (when available). While NSVB did not directly update models for trees that are considered woodland species or trees within the Pacific (USDA Forest Service 2022a,b) and Caribbean Islands (collectively referred to hereafter as 'non-NSVB trees'), volume, biomass, and carbon estimates for these trees have also changed. For non-NSVB trees, the standardization of tree defects and how variables are reported (i.e., whether models for total-stem or merchantable-bole volumes are available) may be reflected as differences in volume estimates. Additionally, biomass estimates for non-NSVB trees are based on regional biomass models and no longer are adjusted as they were under the CRM. Finally, updates to carbon fractions (when available) and calculation of aboveground biomass are reflected in aboveground and belowground biomass carbon estimates. If inventory plots included data on individual trees, a new method was implemented to estimate aboveground biomass carbon (Westfall et al. In press).

Understory vegetation

Understory vegetation is a minor component of total forest ecosystem biomass. Understory vegetation is defined as all biomass of undergrowth plants in a forest, including woody shrubs and trees less than 2.54 cm dbh. In this *Inventory*, it is assumed that 10 percent of understory carbon mass is belowground. This general root-to-shoot ratio (0.11) is near the

lower range of temperate forest values provided in IPCC (2006) and was selected based on two general assumptions: ratios are likely to be lower for light-limited understory vegetation as compared with larger trees, and a greater proportion of all root mass will be less than 2 mm diameter.

Estimates of carbon density are based on information in Birdsey (1996), which was applied to FIA permanent plots. These were fit to the model below:

Equation A-46: Ratio of Understory Carbon Density to Live Tree Carbon Density

$$\text{Ratio} = e^{(A - B \times \ln(\text{live tree C density}))} \quad (1)$$

Where “e” = exponential function, “A” and “B” are model coefficients and “ln(live tree C density)” = log base e. In this model, the ratio is the ratio of understory C density (T C/ha) to live tree carbon density (above- and below-ground) according to Jenkins et al. (2003) and expressed in T C/ha. An additional coefficient is provided as a maximum ratio; that is, any estimate predicted from the model that is greater than the maximum ratio is set equal to the maximum ratio. A full set of coefficients are in Table A-195. Regions and forest types are the same classifications described in Smith et al. (2003). As an example, the basic calculation for understory carbon in aspen-birch forests in the Northeast is:

Equation A-47: Understory Carbon Density

$$\text{Understory (T C/ha)} = (\text{live tree C density}) \times e^{(0.855 - 1.03 \times \ln(\text{tree C density}))} \quad (2)$$

This calculation is followed by three possible modifications. First, the maximum value for the ratio is set to 2.02 (see value in Table A-201 column “maximum ratio”); this also applies to stands with zero tree carbon, which is undefined in the above model. Second, the minimum ratio is set to 0.005 (Birdsey 1996). Third, nonstocked (i.e., currently lacking tree cover but still in the forest land use) and pinyon/juniper forest types (see Table A-194) are set to coefficient A, which is a carbon density (T C/ha) for these types only.

Table A-195: Coefficients for Estimating the Ratio of Carbon Density of Understory Vegetation (above- and belowground, T C/ha) by Region and Forest Type^a

Region ^b	Forest Type ^b	A	B	Maximum ratio ^c
NE	Aspen-Birch	0.855	1.032	2.023
	MBB/Other Hardwood	0.892	1.079	2.076
	Oak-Hickory	0.842	1.053	2.057
	Oak-Pine	1.960	1.235	4.203
	Other Pine	2.149	1.268	4.191
	Spruce-Fir	0.825	1.121	2.140
	White-Red-Jack Pine	1.000	1.116	2.098
	Nonstocked	2.020	2.020	2.060
NLS	Aspen-Birch	0.777	1.018	2.023
	Lowland Hardwood	0.650	0.997	2.037
	Maple-Beech-Birch	0.863	1.120	2.129
	Oak-Hickory	0.965	1.091	2.072
	Pine	0.740	1.014	2.046
	Spruce-Fir	1.656	1.318	2.136
	Nonstocked	1.928	1.928	2.117
NPS	Conifer	1.189	1.190	2.114
	Lowland Hardwood	1.370	1.177	2.055
	Maple-Beech-Birch	1.126	1.201	2.130
	Oak-Hickory	1.139	1.138	2.072
	Oak-Pine	2.014	1.215	4.185
	Nonstocked	2.052	2.052	2.072
PSW	Douglas-fir	2.084	1.201	4.626
	Fir-Spruce	1.983	1.268	4.806
	Hardwoods	1.571	1.038	4.745
	Other Conifer	4.032	1.785	4.768
	Pinyon-Juniper	4.430	4.430	4.820
	Redwood	2.513	1.312	4.698
	Nonstocked	4.431	4.431	4.626

PWE	Douglas-fir	1.544	1.064	4.626
	Fir-Spruce	1.583	1.156	4.806
	Hardwoods	1.900	1.133	4.745
	Lodgepole Pine	1.790	1.257	4.823
	Pinyon-Juniper	2.708	2.708	4.820
	Ponderosa Pine	1.768	1.213	4.768
	Nonstocked	4.315	4.315	4.626
PWW	Douglas-fir	1.727	1.108	4.609
	Fir-Spruce	1.770	1.164	4.807
	Other Conifer	2.874	1.534	4.768
	Other Hardwoods	2.157	1.220	4.745
	Red Alder	2.094	1.230	4.745
	Western Hemlock	2.081	1.218	4.693
	Nonstocked	4.401	4.401	4.589
RMN	Douglas-fir	2.342	1.360	4.731
	Fir-Spruce	2.129	1.315	4.749
	Hardwoods	1.860	1.110	4.745
	Lodgepole Pine	2.571	1.500	4.773
	Other Conifer	2.614	1.518	4.821
	Pinyon-Juniper	2.708	2.708	4.820
	Ponderosa Pine	2.099	1.344	4.776
Nonstocked	4.430	4.430	4.773	
RMS	Douglas-fir	5.145	2.232	4.829
	Fir-Spruce	2.861	1.568	4.822
	Hardwoods	1.858	1.110	4.745
	Lodgepole Pine	3.305	1.737	4.797
	Other Conifer	2.134	1.382	4.821
	Pinyon-Juniper	2.757	2.757	4.820
	Ponderosa Pine	3.214	1.732	4.820
Nonstocked	4.243	4.243	4.797	
SC	Bottomland Hardwood	0.917	1.109	1.842
	Misc. Conifer	1.601	1.129	4.191
	Natural Pine	2.166	1.260	4.161
	Oak-Pine	1.903	1.190	4.173
	Planted Pine	1.489	1.037	4.124
	Upland Hardwood	2.089	1.235	4.170
	Nonstocked	4.044	4.044	4.170
SE	Bottomland Hardwood	0.834	1.089	1.842
	Misc. Conifer	1.601	1.129	4.191
	Natural Pine	1.752	1.155	4.178
	Oak-Pine	1.642	1.117	4.195
	Planted Pine	1.470	1.036	4.141
	Upland Hardwood	1.903	1.191	4.182
	Nonstocked	4.033	4.033	4.182

^a Prediction of ratio of understory carbon to live tree carbon is based on the model: $\text{Ratio} = \exp(A - B \times \ln(\text{tree_C_density}))$, where “ratio” is the ratio of understory carbon density to live tree (above-and below-ground) carbon density, and “tree_C_density” is live tree (above-and below-ground) carbon density in T C/ha. Note that this ratio is multiplied by tree carbon density on each plot to produce understory vegetation.

^b Regions and types as defined in Smith et al. (2003).

^c Maximum ratio: any estimate predicted from the model that is greater than the maximum ratio is set equal to the maximum ratio.

Dead Wood

The standing dead tree estimates are primarily based on plot-level measurements (Westfall et al. 2023, Woodall et al. 2011). This carbon pool includes aboveground and belowground (coarse root) mass and includes trees of at least 2.54 cm dbh. Calculations follow the basic methods applied to live trees (Westfall et al. In press) with additional modifications to

account for decay (Harmon et al. 2011). Carbon fractions by decay class and hardwood and softwood are used for standing dead trees (Westfall et al. In press).

Downed dead wood, inclusive of logging residue, are sampled on a subset of NFI plots. Despite a reduced sample intensity, a single down woody material population estimate (Woodall et al. 2010; Domke et al. 2013; Woodall et al. 2013) per state is now incorporated into these empirical downed dead wood estimates. Downed dead wood is defined as pieces of dead wood greater than 7.5 cm diameter, at transect intersection, that are not attached to live or standing dead trees. It also includes stumps and roots of harvested trees. Ratio estimates of downed dead wood to live tree biomass were developed using FORCARB2 simulations and applied at the plot level (Smith et al. 2004). Estimates for downed dead wood correspond to the region and forest type classifications described in Smith et al. (2003). A full set of ratios is provided in Table A-196. An additional component of downed dead wood is a regional average estimate of logging residue based on Smith et al. (2006) applied at the plot level. These are based on a regional average carbon density at age zero and first order decay; initial densities and decay coefficients are provided in Table A-197. These amounts are added to explicitly account for downed dead wood following harvest. The sum of these two components is then adjusted by the ratio of population totals; that is, the ratio of plot-based to modeled estimates (Domke et al. 2013). An example of this 3-part calculation for downed dead wood in a 25-year-old naturally regenerated loblolly pine forest with 82.99 T C/ha in live trees (Jenkins et al. 2003) in Louisiana is as follows:

First, an initial estimate from live tree carbon density and Table A-196 (SC, Natural Pine)

Equation A-48: Carbon Density of Downed Dead Wood

$$C \text{ density} = 82.99 \times 0.068 = 5.67 \text{ (T C/ha)}$$

Second, an average logging residue from age and Table A-196 (SC, softwood)

Equation A-49: Logging Residue Carbon Density

$$C \text{ density} = 5.5 \times e(-25/17.9) = 1.37 \text{ (T C/ha)}$$

Third, adjust the sum by the downed dead wood ratio plot-to-model for Louisiana, which was 27.6/31.1 = 0.886

Equation A-50: Adjusted Carbon Density of Downed Dead Wood

$$C \text{ density} = (5.67 + 1.37) \times 0.886 = 6.24 \text{ (T C/ha)}$$

Table A-196: Ratio for Estimating Downed Dead Wood by Region and Forest Type

Region ^a	Forest type ^a	Ratio ^b
NE	Aspen-Birch	0.078
	MBB/Other Hardwood	0.071
	Oak-Hickory	0.068
	Oak-Pine	0.061
	Other Pine	0.065
	Spruce-Fir	0.092
	White-Red-Jack Pine	0.055
	Nonstocked	0.019
NLS	Aspen-Birch	0.081
	Lowland Hardwood	0.061
	Maple-Beech-Birch	0.076
	Oak-Hickory	0.077
	Pine	0.072
	Spruce-Fir	0.087
NPS	Nonstocked	0.027
	Conifer	0.073
	Lowland Hardwood	0.069
	Maple-Beech-Birch	0.063
	Oak-Hickory	0.068
PSW	Oak-Pine	0.069
	Nonstocked	0.026
	Douglas-fir	0.091

	Fir-Spruce	0.109
	Hardwoods	0.042
	Other Conifer	0.100
	Pinyon-Juniper	0.031
	Redwood	0.108
	Nonstocked	0.022
PWE	Douglas-fir	0.103
	Fir-Spruce	0.106
	Hardwoods	0.027
	Lodgepole Pine	0.093
	Pinyon-Juniper	0.032
	Ponderosa Pine	0.103
	Nonstocked	0.024
PWW	Douglas-fir	0.100
	Fir-Spruce	0.090
	Other Conifer	0.073
	Other Hardwoods	0.062
	Red Alder	0.095
	Western Hemlock	0.099
	Nonstocked	0.020
RMN	Douglas-fir	0.062
	Fir-Spruce	0.100
	Hardwoods	0.112
	Lodgepole Pine	0.058
	Other Conifer	0.060
	Pinyon-Juniper	0.030
	Ponderosa Pine	0.087
Nonstocked	0.018	
RMS	Douglas-fir	0.077
	Fir-Spruce	0.079
	Hardwoods	0.064
	Lodgepole Pine	0.098
	Other Conifer	0.060
	Pinyon-Juniper	0.030
	Ponderosa Pine	0.082
Nonstocked	0.020	
SC	Bottomland Hardwood	0.063
	Misc. Conifer	0.068
	Natural Pine	0.068
	Oak-Pine	0.072
	Planted Pine	0.077
	Upland Hardwood	0.067
	Nonstocked	0.013
SE	Bottomland Hardwood	0.064
	Misc. Conifer	0.081
	Natural Pine	0.081
	Oak-Pine	0.063
	Planted Pine	0.075
	Upland Hardwood	0.059
Nonstocked	0.012	

^a Regions and types as defined in Smith et al. (2003).

^b The ratio is multiplied by the live tree carbon density on a plot to produce downed dead wood carbon density (T C/ha).

Table A-197: Coefficients for Estimating Logging Residue Component of Downed Dead Wood

Region ^a	Forest Type Group ^b (softwood/hardwood)	Initial C Density (T/ha)	Decay Coefficient
Alaska	hardwood	6.9	12.1
Alaska	softwood	8.6	32.3
NE	hardwood	13.9	12.1
NE	softwood	12.1	17.9
NLS	hardwood	9.1	12.1
NLS	softwood	7.2	17.9
NPS	hardwood	9.6	12.1
NPS	softwood	6.4	17.9
PSW	hardwood	9.8	12.1
PSW	softwood	17.5	32.3
PWE	hardwood	3.3	12.1
PWE	softwood	9.5	32.3
PWW	hardwood	18.1	12.1
PWW	softwood	23.6	32.3
RMN	hardwood	7.2	43.5
RMN	softwood	9.0	18.1
RMS	hardwood	5.1	43.5
RMS	softwood	3.7	18.1
SC	hardwood	4.2	8.9
SC	softwood	5.5	17.9
SE	hardwood	6.4	8.9
SE	softwood	7.3	17.9

^a Regions are defined in Smith et al. (2003) with the addition of coastal Alaska.

^b Forest types are according to majority hardwood or softwood species.

Litter carbon

Carbon in the litter layer is currently sampled on a subset of the NFI plots. Litter carbon is the pool of organic carbon (including material known as duff, humus, and fine woody debris) above the mineral soil and includes woody fragments with diameters of up to 7.5 cm. Because litter attributes are only collected on a subset of NFI plots, a model (3) was developed to predict carbon density based on plot/site variables for plots that lacked litter information (Domke et al. 2016):

Equation A-51: Litter Carbon density

$$P(FFCFull) = f(lat, lon, elev, fortypgrp, above, ppt, tmax, gmi) + u \quad (3)$$

where,

- lat = latitude,
- lon = longitude,
- elev = elevation,
- fortypgrp = forest type group,
- above = aboveground live tree C (trees ≥ 2.54 cm dbh),
- ppt = mean annual precipitation,
- tmax = average maximum temperature,
- gmi = the ratio of precipitation to potential evapotranspiration,
- u = the uncertainty in the prediction resulting from the sample-based estimates of the model parameters and observed residual variability around this prediction.

Due to data limitations in certain regions and inventory periods, a series of reduced non-parametric models, which did not include climate variables, were used rather than replacing missing variables with imputation techniques. Database records used to compile estimates for this report were grouped by variable availability and the approaches described herein were applied. Litter carbon predictions are expressed as density (T ha⁻¹).

Soil organic carbon

This section provides a summary of the methodology used to predict SOC for this report. A complete description of the approach is in Domke et al. (2017). The data used to develop the modeling framework to predict SOC on forest land came from the NFI and the International Soil Carbon Network. Since 2001, the FIA program has collected soil samples on every 16th base intensity plot (approximately every 2,428 ha) distributed approximately every 38,848 ha, where at least one forested condition exists (Woodall et al. 2010). On fully forested plots, mineral and organic soils were sampled adjacent to subplots 2 by taking a single core at each location from two layers: 0 to 10.16 cm and 10.16 to 20.32 cm. The texture of each soil layer was estimated in the field, and physical and chemical properties were determined in the laboratory (U.S. Forest Service 2011). For this analysis, estimates of SOC from the NFI were calculated following O'Neill et al. (2005):

Equation A-52: Total mass of mineral and organic soil carbon

$$\sum SOC_{FIA_TOTAL} = C_i \cdot BD_i \cdot t_i \cdot ucf \quad (4)$$

where,

$$\begin{aligned} \sum SOC_{FIA_TOTAL} &= \text{total mass (Mg C ha}^{-1}\text{) of the mineral and organic soil C over all } i\text{th layers,} \\ C_i &= \text{percent organic C in the } i\text{th layer,} \\ BD_i &= \text{bulk density calculated as weight per unit volume of soil (g-cm}^{-3}\text{) at the } i\text{th soil layer,} \\ t_i &= \text{thickness (cm) of the } i\text{th soil layer (either 0 to 10.16 cm or 10.16 to 20.32 cm), and} \\ ucf &= \text{unit conversion factor (100).} \end{aligned}$$

The SOC_{FIA_TOTAL} estimates from each plot were assigned by forest condition on each plot, resulting in 3,667 profiles with SOC layer observations at 0 to 10.16 and 10.16 to 20.32 cm depths. Since the United States has historically reported SOC estimates to a depth of 100 cm (Heath et al. 2011, USEPA 2015), International Soil Carbon Monitoring Network (ISCN) data from forests in the United States were harmonized with the FIA soil layer observations to develop model functions of SOC by soil order to a depth of 100 cm. All observations used from the ISCN were contributed by the Natural Resources Conservation Service. A total of 16,504 soil layers from 2,037 profiles were used from ISCN land uses defined as deciduous, evergreen, or mixed forest. The FIA-ISCN harmonized dataset used for model selection and prediction included a total of 5,704 profiles with 23,838 layer observations at depths ranging from 0 to 1,148 cm. The modeling framework developed to predict SOC for this report was built around strategic-level forest and soil inventory information and auxiliary variables available for all FIA plots in the United States. The first phase of the new estimation approach involved fitting models using the midpoint of each soil layer from the harmonized dataset and SOC estimates at those midpoints. Several linear and nonlinear models were evaluated, and a log-log model provided the optimal fit to the harmonized data:

Equation A-53: Soil organic carbon at midpoint depth

$$\log_{10} SOC_i = I + \log_{10} Depth \quad (5)$$

where,

$$\begin{aligned} \log_{10} SOC_i &= \text{SOC density (Mg C ha}^{-1}\text{ cm depth}^{-1}\text{) at the midpoint depth,} \\ I &= \text{intercept,} \\ \log_{10} Depth &= \text{profile midpoint depth (cm).} \end{aligned}$$

The model was validated by partitioning the complete harmonized dataset multiple times into training and testing groups and then repeating this step for each soil order to evaluate model performance by soil order. Extra sum of squares F tests were used to evaluate whether there were statistically significant differences between the model coefficients from the model fit to the complete harmonized dataset and models fit to subsets of the data by soil order. Model coefficients for each soil order were used to predict SOC for the 20.32 to 100 cm layer for all FIA plots with soil

profile observations. Next, the SOC layer observations from the FIA and predictions over the 100 cm profile for each FIA plot were summed:

Equation A-54: Total soil organic carbon density

$$SOC_{100} = SOC_{FIA_TOTAL} + SOC_{20-100} \quad (6)$$

where,

$$SOC_{100} = \text{total estimated SOC density from 0-100 cm for each forest condition with a soil sample in the FIA database,}$$

$$SOC_{FIA_TOTAL} \text{ as previously defined in model (4), } SOC_{20-100} = \text{predicted SOC from 20.32 to 100 cm from model (5).}$$

In the second phase of the modeling framework, SOC_{100} estimates for FIA plots were used to predict SOC for plots lacking SOC_{100} estimates using a non-parametric model; this particular machine learning tool used bootstrap aggregating (i.e., bagging) to develop models to improve prediction (Breimen 2001). It also relies on random variable selection to develop a forest of uncorrelated regression trees. These trees recognize the relationship between a dependent variable, in this case SOC_{100} , and a set of predictor variables. All relevant predictor variables—those that may influence the formation, accumulation, and loss of SOC—from annual inventories collected on all base intensity plots and auxiliary climate, soil, and topographic variables obtained from the PRISM climate group (Northwest Alliance 2015), Natural Resources Conservation Service (NRCS 2015), and U.S. Geological Survey (Danielson and Gesch 2011), respectively, were included in the analysis. Due to regional differences in sampling protocols, many of the predictor variables included in the variable selection process were not available for all base intensity plots. To avoid problems with data limitations, pruning was used to reduce the models to the minimum number of relevant predictors (including both continuous and categorical variables) without substantial loss in explanatory power or increase in root mean squared error (RMSE). The general form of the full non-parametric models were:

Equation A-55: Predicted soil organic carbon

$$P(SOC) = f(lat, lon, elev, fortypgrp, ppt, t max, g mi, order, surfgeo) \quad (7)$$

where,

P(SOC)	= predicted soil organic carbon per hectare to a depth of 100 cm
lat	= latitude,
lon	= longitude,
elev	= elevation,
fortypgrp	= forest type group,
ppt	= mean annual precipitation,
t max	= average maximum temperature,
g mi	= the ratio of precipitation to potential evapotranspiration,
order	= soil order,
surfgeo	= surficial geological description

Compilation of population estimates using NFI plot data

Methods for the conterminous United States and Coastal Alaska

The estimation framework is fundamentally driven by the annual NFI. Unfortunately, the annual NFI does not extend to 1990 and the periodic data from the NFI are not consistent (e.g., different plot design) with the annual NFI necessitating the adoption of a system to predict the annual carbon parameters back to 1990. To facilitate the carbon prediction parameters, the estimation framework is comprised of a forest dynamics module (age transition matrices) and a land-use dynamics module (land area transition matrices). The forest dynamics module assesses forest uptake, forest aging, and disturbance effects (i.e., disturbances such as wind, fire, and floods identified by foresters on inventory plots). The land use dynamics module assesses carbon stock transfers associated with afforestation and deforestation (e.g., Woodall et al. 2015b). Both modules are developed from land use area statistics and carbon stock change or carbon stock transfer by age class. The required inputs are estimated from more than 625,000 forest and nonforest observations in the NFI database (U.S. Forest Service 2023a-c). Model predictions for before or after the annual NFI period are constructed from

the estimation framework using only the annual observations. This modeling framework includes opportunities for user-defined scenarios to evaluate the impacts of land-use change and disturbance rates on future carbon stocks and stock changes. As annual NFIs have largely completed at least one cycle and have been remeasured, age and area transition matrices can be empirically informed. In contrast, as annual inventories in Wyoming are still undergoing their first complete cycle, they are still in the process of being remeasured, and as a result theoretical transition matrices need to be developed.

Wear and Coulston (2015) and Coulston et al. (2015) provide the framework for the model. The overall objective is to estimate unmeasured historical changes and future changes in forest carbon parameters consistent with annual NFI estimates. For most regions, forest conditions are observed at time t_0 and at a subsequent time $t_1 = t_0 + s$, where s is the time step (time measured in years) and is indexed by discrete (5 year) forest age classes. The inventory from t_0 is then predicted back to the year 1990 and projected from t_1 to 2022. This prediction approach requires simulating changes in the age-class distribution resulting from forest aging and disturbance events and then applying carbon density estimates for each age class. For all states in the conterminous United States (except for Wyoming), age class transition matrices are estimated from observed changes in age classes between t_0 and t_1 . In Wyoming, only one inventory was available (t_0) so transition matrices were obtained from theory but informed by the condition of the observed inventory to predict from t_0 to 1990 and predict from t_0 to 2022.

Theoretical Age Transition Matrices

Without any mortality-inducing disturbance, a projection of forest conditions would proceed by increasing all forest ages by the length of the time step until all forest resided in a terminal age class where the forest is retained indefinitely (this is, by assumption, where forest carbon per unit area reaches a stable maximum). For the most basic case, disturbances (e.g., wildfire or timber harvesting) can reset some of the forest to the first age class. Disturbance can also alter the age class in more subtle ways. If a portion of trees in a multiple-age forest dies, the trees comprising the average age calculation change, thereby shifting the average age higher or lower (generally by one age class).

With n age classes, the age transition matrix (\mathbf{T}) is an $n \times n$ matrix, and each element (\mathbf{T}_{qr}) defines the proportion of forest area in class q transitioning to class r during the time step (s). The values of the elements of \mathbf{T} depend on a number of factors, including forest disturbances such as harvests, fire, storms, and the value of s , especially relative to the span of the age classes. For example, holding area fixed, allowing for no mortality, defining the time step s equivalent to the span of age classes, and defining five age classes results in,

Equation A-56: Example age transition matrix

$$\mathbf{T} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \end{pmatrix} \quad (8)$$

where all forest area progresses to the next age class and forests within the terminal age class are retained forever. With this version of \mathbf{T} , after five time steps all forests would be in the terminal age class. Relaxing these assumptions changes the structure of \mathbf{T} . If all disturbances, including harvesting and fire, that result in stand regeneration are accounted for and stochastic elements in forest aging are allowed, \mathbf{T} defines a traditional Lefkovitch matrix population model (e.g., Caswell 2001) and becomes,

$$\mathbf{T} = \begin{pmatrix} 1 - t_1 - d_1 & d_2 & d_3 & d_4 & d_5 \\ t_1 & 1 - t_2 - d_2 & 0 & 0 & 0 \\ 0 & t_2 & 1 - t_3 - d_3 & 0 & 0 \\ 0 & 0 & t_3 & 1 - t_4 - d_4 & 0 \\ 0 & 0 & 0 & t_4 & 1 - d_5 \end{pmatrix} \quad (9)$$

where t_q is the proportion of forest of age class q transitioning to age class $q+1$, d_q is the proportion of age class q that experiences a stand-replacing disturbance, and $(1 - t_q - d_q)$ is the proportion retained within age class q (\mathbf{T}_{qr}).

Projections and Backcast for Wyoming

Projections of forest carbon in Wyoming are based on a life stage model:

Equation A-57: Carbon Stock Change

$$\Delta C_t = C_{t+m} - C_t = (F_t T - F_t) \cdot \text{Den} + L_t \cdot \text{Den} \quad (10)$$

In this framework **T** is an age transition matrix that shifts the age distribution of the forest **F**. The difference in forest area by age class between time t and $t+s$ is $F_t T - F_t$. This quantity is multiplied by carbon density by age class (**Den**) to estimate carbon stock change of forest remaining forest between t and $t+s$. Land-use change is accounted for by the addition of $L_t \cdot \text{Den}$, where L_t identifies the age distribution of net land shifts into or out of forests. A query of the forest inventory databases provides estimates of **F** and **Den**, while inventory observations and modeling assumptions are used to estimate **T**. By expanding **Den** to a matrix of carbon contained in all the constituent pools of forest carbon, projections for all pools are generated.

Land-use change is incorporated as a $1 \times n$ vector **L**, with positive entries indicating increased forest area and negative entries indicating loss of forest area, which provides insights of net change only. Implementing a forest area change requires some information and assumptions about the distribution of the change across age classes (the n dimension of **L**). In the eastern states, projections are based on the projection of observed gross area changes by age class. In western states, total forest area changes are applied using rules. When net gains are positive, the area is added to the youngest forest age class; when negative, area is subtracted from all age classes in proportion to the area in each age class category.

Backcasting forest carbon inventories generally involve the same concepts as forecasting. An initial age class distribution is shifted at regular time steps backwards through time, using a transition matrix (**B**):

Equation A-58: Backcasting Age Class Distribution

$$F_{t-s} = F_t \cdot B \quad (11)$$

B is constructed based on similar logic used for creating **T**. The matrix cannot simply be derived as the inverse of **T** ($F_{t-s} = F_t T^{-1}$) because of the accumulating final age class (i.e., **T** does not contain enough information to determine the proportion of the final age class derived from the $n-1$ age class and the proportion that is retained in age class n from the previous time step).¹¹³ However, **B** can be constructed using observed changes from the inventory and assumptions about transition/accumulation including nonstationary elements of the transition model:

Equation A-59: Age Transition Model

$$B = \begin{pmatrix} 1 - \sum_q d_q & b_2 & 0 & 0 & 0 \\ d_1 & 1 - b_2 & b_3 & 0 & 0 \\ d_2 & 0 & 1 - b_3 & b_4 & 0 \\ d_3 & 0 & 0 & 1 - b_4 & b_r \\ d_4 & 0 & 0 & 0 & 1 - b_r \end{pmatrix} \quad (12)$$

Forest area changes need to be accounted for in the backcasts as well:

Equation A-60: Forest Area Change

$$F_{t-s} = F_t B - L_t \quad (13)$$

Where L_t is the forest area change between t_1 and t_0 as previously defined.

¹¹³ Simulation experiments show that a population that evolves as a function of **T** can be precisely predicted using T^{-1} . However, applying the inverse to a population that is not consistent with the long-run outcomes of the transition model can result in predictions of negative areas within some stage age classes.

In Wyoming, the theoretical life-stage models described by matrices (9) and (10) were applied. The disturbance factors (d) in both **T** and **B** are obtained from the current NFI by assuming that the area of forest in age class 1 resulted from disturbance in the previous period, the area in age class 2 resulted from disturbance in the period before that, and so on. The source of disturbed forest was assumed to be proportional to the area of forest in each age class. For projections (**T**), the average of implied disturbance for the previous two periods was applied. For the backcast (**B**), the disturbance frequencies implied by the age class distribution for each time step are moved. For areas with empirical transition matrices, change in forest area (L_t) was backcasted/projected using the change in forest area observed for the period t_0 to t_1 .

Projections and Backcast for the Conterminous United States (excluding Wyoming) and coastal Alaska

For all states in the conterminous United States (with the exception of Wyoming) and coastal Alaska remeasured plots were available. When remeasured data are available, the previously described approach is extended to estimate change more directly; in this case $\Delta C_t = F_t \times \delta C$, where ΔC is net stock change by pool within the analysis area, F is as previously defined, and δC is an $n \times cp$ matrix of per unit area forest carbon stock change per year by pool (cp) arrayed by forest age class. Inter-period forest carbon dynamics are previously described, and the age transition matrix (T) is estimated from the observed data directly. Forest carbon change at the end of the next period is defined as: $\Delta C_{t+s} = F_t \times T \times \delta C$. Land-use change and disturbances such as cutting, fire, weather, insects, and diseases were incorporated by generalizing to account for the change vectors and undisturbed forest remaining as undisturbed forest:

Equation A-61: Land Use Change and Disturbance

$$\Delta C_{t+s} = \sum_{d \in L} (A_{td} \cdot T_d \cdot \delta C_d) \quad (14)$$

Where A_{td} = area by age class of each mutually exclusive land category in L which includes d disturbances at time t .

$L = (FF, NFF, FNF, Fcut, Ffire, Fweather, Fid)$ where FF =undisturbed forest remaining as undisturbed forest, NFF =nonforest to forest conversion, FNF =forest to nonforest conversion, $Fcut$ =cut forest remaining as forest, $Ffire$ =forest remaining as forest disturbed by fire, $Fweather$ =forest remaining as forest disturbed by weather, and Fid =forest remaining as forest disturbed by insects and diseases. In the case of land transfers (FNF and NFF), T_d is an $n \times n$ identity matrix and δC_d is a carbon stock transfer rate by age. Paired measurements for all plots in the inventory provide direct estimates of all elements of δC , T_d , and A_{td} matrices.

Predictions are developed by specifying either F_{t+s} or A_{t+sd} for either a future or a past state. To move the system forward, T is specified so that the age transition probabilities are set up as the probability between a time 0 and a time 1 transition. To move the system backward, T is replaced by B so that the age transition probabilities are for transitions from time 1 to time 0. Forecasts were developed by assuming the observed land-use transitions and disturbance rates would continue for the next 5 years. Predictions moving back in time were developed using a Markov Chain process for land-use transitions and observed disturbance rates for fire, weather, and insects. Historical forest cutting was incorporated by using the relationship between the area of forest cutting estimated from the inventory plots and the volume of roundwood production from the Timber Products Output program (U.S. Forest Service 2023d). This relationship allowed for the modification of $Fcut$ such that it followed trends described by Oswald et al. (2019).

Methods for Interior Alaska

Inventory and sampling

In 2014, a pilot inventory was established in the Tanana Valley State Forest and Tetlin National Wildlife Refuge in Interior Alaska. This pilot inventory was a collaboration between the USDA Forest Service, FIA program, the National Aeronautical and Space Administration (NASA), and many other federal, state, and local partners. This effort resulted in the establishment of 98 field plots which were measured during the summer of 2014 and integrated with NASA's Goddard LiDAR/Hyperspectral/Thermal (G-LiHT) imaging system. Given the remote nature of Interior Alaska forest, the NFI plots in the pilot campaign were sampled at a lower intensity than base NFI plots (1 plot per 2403 ha) in the conterminous United States and coastal Alaska. Several plot-level protocols were also adapted to accommodate the unique conditions of forests in this region (see Pattison et al. 2018 for details on plot design and sampling protocols). The pilot field campaign became operational in 2016 and plots measured on a 1/5 intensity (1 plot per 12013 ha) from 2014, 2016 to 2022 from the Interior Alaska NFI were used ($n = 1031$).

A spatially balanced sampling design was used to identify field sample locations across interior Alaska following standard FIA procedures with a tessellation of hexagons and one sample plot selected per hexagon – 1/5 intensity in interior

Alaska (Bechtold and Patterson 2005). The sampling locations were classified as forest or non-forest using the NLCD from 2001 and 2011. It is important to note that this is different from the process for classifying NFI plots into land cover and land-use categories in the conterminous United States where high resolution areal imagery is used. Since the fine-scale remotely sensed imagery (National Agriculture Imagery Program; NAIP 2015) used in the conterminous United States were not available for Alaska and given that the NLCD has been used to classify land use categories in Alaska in the Representation of the U.S. Land Base in this *Inventory*, the NLCD was the most consistent and credible option for classification. Next, the forest land was further classified as managed or unmanaged following the definition in the Representation of the U.S. Land Base and using similar procedures (see Ogle et al. 2018 for details on the managed land layer for the United States).

While only a subset of the total NFI sample was available at the time of this *Inventory*, all NFI plot locations within the sampling frame were used in this analysis. Auxiliary climate, soil, structural, disturbance, and topographic variables were harmonized with each plot location and year of occurrence (if relevant and available) over the entire time series (1990 to 2022).

Prediction

The harmonized data were used to predict plot-level parameters using non-parametric random forests (RF) for regression, a machine learning tool that uses bootstrap aggregating (i.e., bagging) to develop models to improve prediction (Breiman 2001). The RF analysis relies on random variable selection to develop a forest of uncorrelated regression trees. These trees uncover the relationship between a dependent variable (e.g., live aboveground biomass carbon) and a set of predictor variables. The RF analysis included predictor variables ($n > 100$) that may influence carbon stocks within each forest ecosystem pool at each plot location over the entire time series. To avoid problems with data limitations over the time series, variable pruning was used to reduce the RF models to the minimum number of relevant predictors without substantial loss in explanatory power or increase in root mean squared error (RMSE; see Domke et al. 2017). The harmonized dataset used to develop the RF models for each plot-level parameter were partitioned 10 times into training (70 percent) and testing (30 percent) groups and the results were evaluated graphically and with a variety of statistical metrics including Spearman's rank correlation, equivalence tests (Wellek 2003), as well as RMSE. All analyses were conducted using R statistical software (R Core Team 2018).

The RF predictions of carbon stocks for the year 2016 were used as a baseline for plots that have not yet been measured. Next, simple linear regression was used to predict average annual gains/losses by forest ecosystem carbon pool using the chronosequence of plot measurements available at the time of this *Inventory*. These predicted gains/losses were applied over the time series from the year of measurement or the 2016 base year in the case of plots that have not yet been measured. Since the RF predictions of carbon stocks and the predicted gains/losses were obtained from empirical measurements on NFI plots that may have been disturbed at some point over the time series, the predictions inherently incorporate gains/losses associated with natural disturbance and harvesting. That said, there was no evidence of fire disturbance on the plots that have been measured to date. To account for carbon losses associated with fire, carbon stock predictions for plots that have not been measured but were within a fire perimeter, using the same geospatial layers described in the Emissions from Forest Fires section, during the *Inventory* period were adjusted to account for area burned (see Table A-209) and the IPCC (Table 2.6, IPCC 2006) default combustion factor for boreal forests was applied to all live, dead, and litter biomass carbon stocks in the year of the disturbance. The plot-level predictions in each year were then multiplied by the area they represent within the sampling frame to compile population estimates over the time series for this *Inventory*.

Methods for Hawaii and the U.S. Territories

To implement the gain-loss approach in Hawaii and the U.S. Territories, a combination of Tier 1 and Tier 2 methods were applied. All forest land conditions were observed on annual and periodic NFI plots from 2001 to 2019 (see Table A-184 for specific inventories included for each Island). Plot-level data from the NFI were harmonized with data describing ecological zone (FAO 2010), soil attributes (Johnson and Kern 2003, Deenik and McClellan, 2007, IPCC 2019), and dead wood and litter carbon stocks (Oswalt et al. 2008; IPCC 2019). Only estimates of carbon stocks in live trees were consistently available in the NFI for Hawaii and the U.S. Territories for each inventory. These estimates were used to obtain average annual carbon stock change estimates for above and belowground live trees which were applied to each forest plot to capture growth, harvest removals, and mortality. The carbon stocks and annual stock change estimates were compared with country-specific estimates (Oswalt et al. 2008; Selmants et al. 2017), and IPCC (2019) default estimates to ensure they were consistent with other sources. There were limited data available on disturbances and management activities on NFI plots over the times series so Tier 1 methods were applied for dead wood and litter. It was assumed that the average transfer rate into dead wood and litter is equivalent to the average transfer rate out of dead

organic matter so there are no net carbon stock changes included for these pools in the time series (IPCC 2006). Similarly, given data limitations on forest soils and changes on NFI plots over the time series, a Tier 1 approach was also used for soil carbon with country-specific estimates (Johnson and Kern 2003) and IPCC (2019) defaults used to estimate soil carbon stocks with no net carbon stock change reported.

Forest Land Remaining Forest Land Area Estimates

Forest land area estimates in Section 6.2 Forest Land Remaining Forest Land (CRT Category 4A1) of this *Inventory* are compiled using NFI data. Forest land area estimates obtained from these data are also used as part of section 6.1 Representation of the U.S. Land Base (CRT Category 4.1). The forest land area estimates in section 6.2 include Hawaii and the U.S. Territories compiled using different methods than in Section 6.1. The National Land Cover Dataset is used in addition to NRI estimates in Section 6.1 Representation of the U.S. Land Base and forest land in Hawaii are included in that section, but do not include U.S. Territories. Also, it is not possible to separate forest land remaining forest land from land converted to forest land in Wyoming because of the split annual cycle method used for population estimation, this prevents harmonization of forest land in Wyoming with the NRI/NLCD method used in Section 6.1 Representation of the U.S. Land Base (CRT Category 4.1). These issues result in small differences in the managed forest land area in Sections 6.1 and 6.2 of this *Inventory* (Table A-207). There are also other factors contributing to the small differences such as harmonization of aspatial and spatial data across all land-use categories in Section 6.1 over the entire *Inventory* time series.

Carbon in Harvested Wood Products

Estimates of the Harvested Wood Product (HWP) contribution to forest carbon emissions and removals (hereafter called “HWP Contribution”) are based on methods described in Skog (2008) using the WOODCARB II model and the U.S. forest products module (Ince et al. 2011) and many data sources (Table A-198). These methods are based on IPCC (2006) guidance for estimating HWP carbon. The *2006 IPCC Guidelines for National Inventories* provide methods that allow Parties to report the HWP Contribution using one of several different accounting approaches: production, stock change, and atmospheric flow, as well as a default method. The various approaches are described below. The approaches differ in how HWP Contribution is allocated based on production or consumption as well as what processes (atmospheric fluxes or stock changes) are emphasized.

- **Production approach:** Accounts for the net changes in carbon stocks in forests and in the wood products pool, but attributes both to the producing country.
- **Stock-change approach:** Accounts for changes in the product pool within the boundaries of the consuming country.
- **Atmospheric-flow approach:** Accounts for net emissions or removals of carbon to and from the atmosphere within national boundaries. Carbon removal due to forest growth is accounted for in the producing country while carbon emissions to the atmosphere from oxidation of wood products are accounted for in the consuming country.
- **Default approach:** Assumes no change in carbon stocks in HWP. IPCC (2006) requests that such an assumption be justified if this is how a Party is choosing to report.

Table A-198: WOODCARB II inputs, including sources for the data and most recent update.

Harvest wood product	Category	Source(s)	Updated
Softwood			
Lumber	Production	American Forest and Paper Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission;	Current
	Imports	USDC, Bureau of the Census; Western Wood Products Association	
Plywood	Exports		
	Production	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission	Current

Veneer	Production Imports Exports	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission	Current
Other structural panel	Production Imports Exports	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service	Current
Pulpwood-based products	Production Imports Exports	American Plywood Association, The Engineered Wood Association; Composite Panel Association; American Forest and Paper Association; U.S. International Trade Commission; USDA, Foreign Agricultural Service; American Pulpwood Association; United Nations Food and Agriculture Organization	Current
Other industrial products	Production and consumption	USDA, Forest Service; U.S. International Trade Commission	2006
Logs	Imports Exports	Western Wood Products Association; U.S. International Trade Commission	Current
Pulpwood chips	Imports Exports	American Forest and Paper Association; American Pulpwood Association	Current
Fuelwood	Production and consumption	USDA, Forest Service; U.S. International Trade Commission	2006
Hardwood			
Lumber	Production Imports Exports	American Forest and Paper Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission; USDC, Bureau of the Census; Western Wood Products Association	Current
Plywood	Production Imports Exports	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission	Current
Veneer	Production Imports Exports	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service; U.S. International Trade Commission	Current
Other structural panel	Production Imports Exports	American Plywood Association, The Engineered Wood Association; USDA, Foreign Agricultural Service	Current
Pulpwood-based products	Production Imports Exports	American Plywood Association, The Engineered Wood Association; Composite Panel Association; American Forest and Paper Association; U.S. International Trade Commission; USDA, Foreign Agricultural Service; American Pulpwood Association; United Nations Food and Agriculture Organization	Current
Other industrial products	Production and consumption	USDA, Forest Service; U.S. International Trade Commission	2006
Logs	Imports Exports	Western Wood Products Association; U.S. International Trade Commission	Current
Pulpwood chips	Imports Exports	American Forest and Paper Association; American Pulpwood Association	Current
Fuelwood	Production and consumption	USDA, Forest Service; U.S. International Trade Commission	2006
Total			
Paper and board	Production Imports Exports		Current 2020 American Forest and Paper Association 2020
Wood pulp	Production Imports Exports	United Nations Food and Agriculture Organization; American Forest and Paper Association	Current
Recovered paper	Consumption	American Forest and Paper Association	Current
Other fibrous	Consumption	American Forest and Paper Association	Current

Recyclable paper for molded pulp, insulation, and other uses		American Forest and Paper Association	2021
Recyclable paper	Imports	American Forest and Paper Association	2020
	Exports	American Forest and Paper Association	2020
Particleboard	Production	Composite Panel Association	Current
Medium-density fiberboard	Production	Composite Panel Association	Current
Particleboard and medium-density fiberboard	Imports	U.S. International Trade Commission; USDA, Foreign Agricultural Service	Current
	Exports	U.S. International Trade Commission; USDA, Foreign Agricultural Service	Current
Insulating board	Production	American Forest and Paper Association; North American Fiberboard Association	1994
	Imports	American Forest and Paper Association; North American Fiberboard Association	1994
	Exports	American Forest and Paper Association; North American Fiberboard Association	1994
Hardboard	Production	American Forest and Paper Association; U.S. International Trade Commission; Composite Panel Association; U.S. Department of Agriculture, Foreign Agricultural Service	Current
	Imports	American Forest and Paper Association; U.S. International Trade Commission; Composite Panel Association; U.S. Department of Agriculture, Foreign Agricultural Service	Current
	Exports	American Forest and Paper Association; U.S. International Trade Commission; Composite Panel Association; U.S. Department of Agriculture, Foreign Agricultural Service	Current
Recovered fiber pulp	Imports	United Nations Food and Agriculture Organization	Current
	Exports	United Nations Food and Agriculture Organization	Current

The United States uses the production accounting approach (as in previous years) to report HWP Contribution (Table A-199) but estimates for all three approaches are provided in Table A-200. Annual estimates of change are calculated by tracking the additions to (i.e., transfers of harvested wood from the forest ecosystem) and losses from (i.e., the decay of) the pool of products held in end uses (i.e., products in use such as housing or publications) and the pool of products held in solid waste disposal sites (SWDS).

Estimates of five HWP variables that can be used to calculate HWP contribution for the stock change and atmospheric flow approaches for imports and exports are provided in Table A-201. The HWP variables estimated are:

- (1A) Annual change of carbon in wood and paper products in use in the United States,
- (1B) Annual change of carbon in wood and paper products in SWDS in the United States,
- (2A) Annual change of carbon in wood and paper products in use in the United States and other countries where the wood came from trees harvested in the United States,
- (2B) Annual change of carbon in wood and paper products in SWDS in the United States and other countries where the wood came from trees harvested in the United States,
- (3) Carbon in imports of wood, pulp, and paper to the United States,
- (4) Carbon in exports of wood, pulp, and paper from the United States, and
- (5) Carbon in annual harvest of wood from forests in the United States. The sum of these variables yield estimates for HWP contribution under the production accounting approach.

Table A-199: Harvested Wood Products from Wood Harvested in the United States—Annual Additions of Carbon to Stocks and Total Stocks under the Production Approach

Year	Net C additions per year (MMT C per year)			Total C stocks (MMT C)		
	Total	Products in use	Products in SWDS	Total	Products in use	Products in SWDS
1990	(33.8)	(14.9)	(18.8)	1,895	1,249	646
1991	(33.8)	(16.3)	(17.4)	1,929	1,264	665
1992	(32.9)	(15.0)	(17.9)	1,963	1,280	683
1993	(33.4)	(15.9)	(17.5)	1,996	1,295	701
1994	(32.3)	(15.1)	(17.2)	2,029	1,311	718
1995	(30.6)	(14.1)	(16.5)	2,061	1,326	735
1996	(32.0)	(14.7)	(17.3)	2,092	1,340	752
1997	(31.1)	(13.4)	(17.7)	2,124	1,355	769

2017	(110)	(129)	(100)
2018	(108)	(125)	(94)
2019	(106)	(117)	(87)
2020	(128)	(138)	(97)
2021	(129)	(137)	(95)
2022	(131)	(133)	(93)

Note: Parentheses indicate net carbon sequestration (i.e., a net removal of carbon from the atmosphere).

Table A-201: Harvested Wood Products Sectoral Background Data

	1A	1B	2A	2B	3	4	5	6	7	8
<i>Inventory year</i>	Annual Change in stock of HWP in use from consumption	Annual Change in stock of HWP in SWDS from consumption	Annual Change in stock of HWP in use produced from domestic harvest	Annual Change in stock of HWP in SWDS produced from domestic harvest	Annual Imports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood/ chips	Annual Exports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood/ chips	Annual Domestic Harvest	Annual release of C to the atmosphere from HWP consumption (from fuelwood and products in use and products in SWDS)	Annual release of C to the atmosphere from HWP (including firewood) where wood came from domestic harvest (from products in use and products in SWDS)	HWP Contribution to AFOLU CO ₂ emissions/removals
	ΔCHWP IU DC	ΔCHWP SWDS DC	ΔC HWP IU DH	ΔCHWP SWDS DH	PIM	PEX	H	↑CHWP DC	↑CHWP DH	MMT CO ₂ /yr
1990	13.2	18.6	14.9	18.8	11.6	15.6	144.4	108.6	110.7	(123.8)
1995	17.0	16.3	14.1	16.5	16.7	16.7	134.5	101.1	103.9	(112.2)
2000	16.5	17.6	8.7	16.8	22.1	15.3	127.9	100.5	102.4	(93.4)
2005	18.7	18.6	11.6	17.3	25.5	18.8	120.1	89.6	91.2	(106.0)
2010	(2.1)	16.1	2.0	16.8	13.8	25.0	102.7	77.5	83.9	(69.1)
2018	12.0	17.4	7.8	17.8	15.6	20.2	125.7	91.7	100.1	(93.9)
2019	11.5	17.4	6.2	17.5	15.9	18.8	124.4	92.5	100.7	(86.9)
2020	16.9	17.9	8.8	17.6	17.0	19.7	125.9	88.3	99.5	(96.8)
2021	17.1	18.1	8.3	17.5	17.6	19.7	125.0	87.7	99.2	(94.7)
2022	17.4	18.3	7.9	17.4	19.1	19.7	124.1	87.8	98.8	(92.8)

Note: Parentheses indicate net carbon sequestration (i.e., a net removal of carbon from the atmosphere).

Annual estimates of variables 1A, 1B, 2A and 2B were calculated by tracking the additions to and losses from the pool of products held in end uses (e.g., products in uses such as housing or publications) and the pool of products held in SWDS. In the case of variables 2A and 2B, the pools include products exported and held in other countries and the pools in the United States exclude products made from wood harvested in other countries. Solidwood products added to pools include lumber and panels. End-use categories for solidwood include single and multifamily housing, alteration and repair of housing, and other end uses. There is one product category and one end-use category for paper. Additions to and losses from pools are tracked beginning in 1900, with the exception that additions of softwood lumber to housing begins in 1800. Solidwood and paper product production and trade data are from USDA Forest Service and other sources (Hair and Ulrich 1963; Hair 1958; USDC Bureau of Census 1976; Ulrich, 1985, 1989; Steer 1948; AF&PA 2006a, 2006b; Howard 2003, 2007; Howard and Jones 2016; Howard and Liang 2019; AF&PA 2021; AF&PA 2023; FAO 2023).

The rate of transfers or losses from products in use and the rate of decay of products in SWDS are specified by first order (exponential) decay curves with given half-lives (e.g., the time at which half of amount placed in use will have been discarded from use). Half-lives for products in use, determined after calibration of the model to meet two criteria, are shown in Table A-202. The first criterion is that the WOODCARB II model estimate of carbon in houses standing in 2001 needed to match an independent estimate of carbon in housing based on U.S. Census and USDA Forest Service survey data. The second criterion is that the WOODCARB II model estimate of wood and paper being discarded to SWDS needed to match EPA estimates of discards over the period 1990 to 2000. This calibration strongly influences the estimate of variable 1A, and to a lesser extent variable 2A. The calibration also determines the amounts going to SWDS. In addition, WOODCARB II landfill decay rates have been validated by making sure that estimates of methane emissions from landfills based on EPA data are reasonable in comparison to methane estimates based on WOODCARB II landfill decay rates.

Decay parameters for products in SWDS are shown in Table A-203. Estimates of 1B and 2B also reflect the change over time in the fraction of products discarded to SWDS (versus burning or recycling) and the fraction of SWDS that are sanitary landfills versus dumps.

Variables 2A and 2B are used to estimate HWP Contribution under the production accounting approach. A key assumption for estimating these variables is that products exported from the United States and held in pools in other countries have the same half-lives for products in use, the same percentage of discarded products going to SWDS, and the same decay rates in SWDS. Summaries of net fluxes and stocks for harvested wood in products and SWDS are in Table A-201. The decline in net additions to HWP carbon stocks continued through 2009 from the recent high point in 2006. This is due to sharp declines in U.S. production of solidwood and paper products in 2009 primarily due to the decline in housing construction. The low level of gross additions to solidwood and paper products in use in 2009 was exceeded by discards from uses. The result is a net reduction in the amount of HWP carbon that is held in products in use during 2009. For 2009 additions to landfills still exceeded emissions from landfills and the net additions to landfills have remained relatively stable. Overall, there were net carbon additions to HWP in use and in landfills combined.

Table A-202: Half-life of Solidwood and Paper Products in End-Uses

Parameter	Value	Units
Half-life of wood in single family housing 1920 and before	78.0	Years
Half-life of wood in single family housing 1920–1939	78.0	Years
Half-life of wood in single family housing 1940–1959	80.0	Years
Half-life of wood in single family housing 1960–1979	81.9	Years
Half-life of wood in single family housing 1980 +	83.9	Years
Ratio of multifamily half-life to single family half life	0.61	NA
Ratio of repair and alterations half-life to single family half-life	0.30	NA
Half-life for other solidwood product in end uses	38.0	Years
Half-life of paper in end uses	2.54	Years

Source: Skog, K.E. (2008) "Sequestration of C in harvested wood products for the U.S." *Forest Products Journal* 58:56–72. Note that "NA" refers to not applicable.

Table A-206: Forest area (1,000 ha) and Carbon Stocks in Forest Land Remaining Forest Land and Harvested Wood Pools (MMT C)

	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022	2023
Forest Area (1000 ha)	283,500	283,285	283,096	282,521	282,343	281,663	281,137	281,779	281,780	281,752	281,725
Carbon Pools											
Forest Ecosystem	55,142	56,306	57,450	58,536	59,610	61,306	61,519	61,717	61,926	62,130	62,320
Aboveground Biomass	12,739	13,553	14,350	15,122	15,872	17,053	17,199	17,340	17,483	17,622	17,757
Belowground Biomass	2,255	2,413	2,568	2,718	2,864	3,095	3,124	3,151	3,179	3,207	3,233
Dead Wood	1,977	2,158	2,341	2,521	2,704	3,000	3,038	3,074	3,111	3,148	3,184
Litter	3,789	3,799	3,810	3,794	3,787	3,774	3,775	3,767	3,768	3,768	3,761
Soil (Mineral)	28,407	28,404	28,402	28,401	28,402	28,400	28,400	28,400	28,401	28,401	28,401
Soil (Organic)	5,976	5,978	5,979	5,981	5,982	5,983	5,983	5,983	5,983	5,983	5,983
Harvested Wood	1,895	2,061	2,218	2,353	2,462	2,645	2,671	2,694	2,721	2,747	2,772
Products in Use	1,249	1,326	1,395	1,447	1,471	1,516	1,523	1,530	1,538	1,547	1,555
SWDS	646	735	823	906	991	1,130	1,147	1,165	1,182	1,200	1,217
Total Stock	57,037	58,367	59,668	60,890	62,072	63,951	64,189	64,411	64,647	64,877	65,092

Note: Totals may not sum due to independent rounding.

Table A-207: Forest Land Area Estimates and Differences Between Estimates in 6.1 Representation of the U.S. Land Base (CRF Category 4.1) and 6.2 Forest Land Remaining Forest Land (CRT Category 4A1) (kha)

Year	Forest Land (managed) - 6.1 Representation of the U.S. Land Base	Forest Land (managed) - 6.2 Forest Land Remaining Forest Land	Difference between Forest Land Areas (managed) – 6.1 and Forest Land Remaining Forest Land – 6.2 area estimates
1990	281,290	283,500	(2,210)
1995	281,034	283,285	(2,250)
2000	280,785	283,096	(2,310)
2005	280,587	282,521	(1,935)
2010	280,372	282,343	(1,972)
2018	279,683	281,663	(1,981)
2019	279,167	281,137	(1,970)
2020	279,818	281,779	(1,960)
2021	279,829	281,780	(1,950)
2022	279,802	281,752	(1,950)

Note: Parentheses indicate negative values.

Table A-208: State-level Net Carbon Flux from all Forest Pools in Forest Land Remaining Forest Land (MMT C) with Uncertainty Range Relative to Flux Estimate, 2022

State	Stock Change	Lower Bound	Lower Bound (%)	Upper Bound	Upper Bound (%)
Alabama	(13.5)	(15.3)	-14%	(11.6)	14%
Alaska	7.1	(0.0)	-101%	14.2	101%
Arizona	0.6	0.2	-70%	1.0	70%
Arkansas	(9.3)	(10.9)	-17%	(7.8)	17%
California	(8.0)	(16.0)	-100%	0.0	100%
Colorado	2.3	(6.3)	-375%	10.8	375%
Connecticut	(0.8)	(1.1)	-35%	(0.5)	35%
Delaware	(0.0)	(0.1)	-105%	0.0	105%
Florida	(3.4)	(4.0)	-20%	(2.7)	20%
Georgia	(8.8)	(9.3)	-6%	(8.4)	6%
Hawaii	(0.9)	(5.3)	-490%	3.5	490%
Idaho	(0.1)	(3.7)	-2570%	3.4	2570%
Illinois	(2.0)	(3.0)	-51%	(1.0)	51%
Indiana	(3.0)	(4.6)	-53%	(1.4)	53%
Iowa	(1.0)	(1.3)	-32%	(0.7)	32%
Kansas	(0.8)	(1.2)	-53%	(0.4)	53%
Kentucky	(6.2)	(7.8)	-25%	(4.6)	25%
Louisiana	(7.0)	(7.5)	-7%	(6.5)	7%
Maine	(5.1)	(8.1)	-59%	(2.1)	59%
Maryland	(1.4)	(1.9)	-39%	(0.8)	39%
Massachusetts	(1.4)	(1.7)	-27%	(1.0)	27%
Michigan	(5.9)	(9.5)	-60%	(2.4)	60%
Minnesota	(5.3)	(7.6)	-43%	(3.0)	43%
Mississippi	(15.9)	(18.7)	-18%	(13.0)	18%
Missouri	(4.8)	(7.4)	-54%	(2.2)	54%
Montana	1.4	(6.6)	-588%	9.4	588%
Nebraska	(0.3)	(0.3)	-19%	(0.2)	19%
Nevada	(0.1)	(0.3)	-460%	0.2	460%
New Hampshire	(1.7)	(2.3)	-36%	(1.1)	36%
New Jersey	(0.9)	(1.0)	-10%	(0.8)	10%
New Mexico	0.3	(1.7)	-713%	2.2	713%
New York	(8.9)	(11.2)	-26%	(6.6)	26%
North Carolina	(8.9)	(10.1)	-14%	(7.6)	14%

North Dakota	(0.1)	(0.2)	-159%	0.0	159%
Ohio	(3.9)	(6.0)	-53%	(1.8)	53%
Oklahoma	(2.8)	(3.4)	-22%	(2.2)	22%
Oregon	(10.7)	(12.8)	-20%	(8.6)	20%
Pennsylvania	(6.2)	(10.6)	-72%	(1.7)	72%
Rhode Island	(0.1)	(0.3)	-115%	0.0	115%
South Carolina	(4.3)	(4.8)	-13%	(3.7)	13%
South Dakota	0.3	(0.0)	-107%	0.6	107%
Tennessee	(7.8)	(9.3)	-19%	(6.3)	19%
Texas	(10.7)	(11.2)	-5%	(10.2)	5%
Utah	0.4	(1.0)	-337%	1.8	337%
Vermont	(1.7)	(2.4)	-43%	(0.9)	43%
Virginia	(9.8)	(12.5)	-28%	(7.1)	28%
Washington	(4.6)	(9.2)	-100%	0.0	100%
West Virginia	(7.3)	(9.1)	-24%	(5.6)	24%
Wisconsin	(6.5)	(6.9)	-7%	(6.0)	7%
Wyoming	0.2	(0.4)	-319%	0.8	319%
American Samoa	(0.0)	(0.2)	-656%	0.1	656%
Guam	(0.0)	(0.3)	-584%	0.2	584%
Northern					
Mariana Islands	(0.0)	(0.2)	-673%	0.2	673%
Puerto Rico	(0.3)	(2.8)	-780%	2.2	780%
U.S. Virgin					
Islands	(0.0)	(0.2)	-787%	0.1	787%
Total	(189.3)	(209.9)	-11%	(168.8)	11%

Note: Parentheses indicate negative values.

Land Converted to Forest Land

The following section includes a description of the methodology used to estimate stock changes in all forest carbon pools for land converted to forest land. Forest *Inventory* and Analysis data and IPCC (2006) defaults for reference carbon stocks were used to compile separate estimates for the five carbon storage pools within an age class transition matrix for the 20-year conversion period (where possible). The 2017 USDA National Resources *Inventory* (NRI) land-use survey points were classified according to land-use history records starting in 1982 when the NRI survey began. Consequently, the classifications from 1990 to 2001 were based on less than 20 years. Furthermore, the FIA data used to compile estimates of carbon sequestration in the age class transition matrix are based on 5- to 10-yr remeasurements so the exact conversion period was limited to the remeasured data over the time series. Estimates for aboveground and belowground biomass, dead wood and litter were based on data collected from the extensive array of permanent, annual forest inventory plots and associated models (e.g., live tree belowground biomass) in the United States (USDA Forest Service 2023b, 2023c). Carbon conversion factors were applied at the disaggregated level of each inventory plot and then appropriately expanded to population estimates. To ensure consistency in the land converted to forest land category where carbon stock transfers occur between land-use categories, all soil estimates are based on methods from Ogle et al. (2003, 2006) and IPCC (2006).

Live tree carbon pools

Live tree carbon pools include aboveground and belowground (coarse root) biomass of live trees with diameter at breast height (dbh) of at least 2.54 cm at 1.37 m above the forest floor. Separate estimates were made for above and belowground biomass components. If inventory plots included data on individual trees, aboveground tree carbon was based on Westfall et al. (2023). The component ratio method (CRM) which is a function of volume, species, and diameter was used to compile estimates for woodland species where diameter measurements are taken at root collar and belowground biomass carbon for all tree species (Woodall et al. 2011a). An additional component of foliage, which was not explicitly included in Woodall et al. (2011a), was added to each woodland tree following the same CRM method. Carbon is estimated by multiplying the estimated oven-dry biomass by species-specific carbon fraction (Westfall et al. 2023). Complete details are provided in Westfall et al. 2023 and Woodall et al. 2011.

Understory vegetation

Understory vegetation is a minor component of total forest ecosystem biomass. Understory vegetation is defined as all biomass of undergrowth plants in a forest, including woody shrubs and trees less than one-inch dbh. In this *Inventory*, it is assumed that 10 percent of understory carbon mass is belowground. This general root-to-shoot ratio (0.11) is near the lower range of temperate forest values provided in IPCC (2006) and was selected based on two general assumptions: ratios are likely to be lower for light-limited understory vegetation as compared with larger trees, and a greater proportion of all root mass will be less than 2 mm diameter.

Estimates of carbon density are based on information in Birdsey (1996), which was applied to FIA permanent plots. See model (1) in the forest land remaining forest land section of the Annex.

In this model, the ratio is the ratio of understory carbon density (T C/ha) to live tree carbon density (above- and below-ground) according to Jenkins et al. (2003) and expressed in T C/ha. An additional coefficient is provided as a maximum ratio; that is, any estimate predicted from the model that is greater than the maximum ratio is set equal to the maximum ratio. A full set of coefficients are in Table A-195. Regions and forest types are the same classifications described in Smith et al. (2003). An example calculation for understory carbon in aspen-birch forests in the Northeast is provided in the forest land remaining forest land section of the Annex.

This calculation is followed by three possible modifications. First, the maximum value for the ratio is set to 2.02 (see value in column “maximum ratio”); this also applies to stands with zero tree carbon, which is undefined in the above model. Second, the minimum ratio is set to 0.005 (Birdsey 1996). Third, nonstocked (i.e., currently lacking tree cover but still in the forest land use) and pinyon/juniper forest types (see Table A-195) are set to coefficient A, which is a carbon density (T C/ha) for these types only.

Dead wood

The standing dead tree estimates are primarily based on plot-level measurements (Westfall et al. 2023, Woodall et al. 2011). This carbon pool includes aboveground and belowground (coarse root) mass and includes trees of at least 2.54 cm dbh. Calculations follow the basic methods applied to live trees (Westfall et al. 2023, Woodall et al. 2011) with additional modifications to account for decay and structural loss (Harmon et al. 2011). Carbon fractions by decay class and hardwood and softwood are used for standing dead trees (Westfall et al. 2023).

Downed dead wood, inclusive of logging residue, are sampled on a subset of FIA plots. Despite a reduced sample intensity, a single down woody material population estimate (Woodall et al. 2010; Domke et al. 2013; Woodall et al. 2013) per state is now incorporated into these empirical downed dead wood estimates. Downed dead wood is defined as pieces of dead wood greater than 7.5 cm diameter, at transect intersection, that are not attached to live or standing dead trees. It also includes stumps and roots of harvested trees. Ratio estimates of downed dead wood to live tree biomass were developed using FORCARB2 simulations and applied at the plot level (Smith et al. 2004). Estimates for downed dead wood correspond to the region and forest type classifications described in Smith et al. (2003). A full set of ratios is provided in Table A-196. An additional component of downed dead wood is a regional average estimate of logging residue based on Smith et al. (2006) applied at the plot level. These are based on a regional average carbon density at age zero and first order decay; initial densities and decay coefficients are provided in Table A-197. These amounts are added to explicitly account for downed dead wood following harvest. The sum of these two components are then adjusted by the ratio of population totals; that is, the ratio of plot-based to modeled estimates (Domke et al. 2013).

Litter carbon

Carbon in the litter layer is currently sampled on a subset of the NFI plots. Litter carbon is the pool of organic carbon (including material known as duff, humus, and fine woody debris) above the mineral soil and includes woody fragments with diameters of up to 7.5 cm. Because litter attributes are only collected on a subset of NFI plots, a model (3) was developed to predict carbon density based on plot/site variables for plots that lacked litter information (Domke et al. 2016)

Soil organic carbon

A Tier 2 method is applied to estimate mineral soil carbon stock changes for land converted to forest land (Ogle et al. 2003, 2006; IPCC 2006). For this method, land is stratified by climate, soil types, land-use, and land management activity, and then assigned reference carbon levels and factors for the forest land and the previous land use. The difference between the stocks is reported as the stock change under the assumption that the change occurs over 20 years.

Reference carbon stocks have been estimated from data in the National Soil Survey Characterization Database (USDA-NRCS 1997), and U.S.-specific stock change factors have been derived from published literature (Ogle et al. 2003; Ogle et al. 2006). Land use and land use change patterns are determined from a combination of the Forest *Inventory* and Analysis Dataset (FIA), the 2015 National Resources *Inventory* (NRI) (USDA-NRCS 2018), and National Land Cover Dataset (NLCD) (Yang et al. 2018). See Annex 3.12 for more information about this method (Methodology for Estimating N₂O Emissions, CH₄ Emissions and Soil Organic Carbon Stock Changes from Agricultural Soil Management).

Table A-209 summarizes the annual change in mineral soil carbon stocks from U.S. soils that were estimated using a Tier 2 method (MMT C/year). The range is a 95 percent confidence interval estimated from the standard deviation of the NRI sampling error and uncertainty associated with the 1000 Monte Carlo simulations (See Annex 3.12). Table A-211 summarizes the total land areas by land use/land-use change subcategory that were used to estimate soil C stock changes for mineral soils between 1990 and 2015.

Land Converted to Forest Land Area Estimates

Forest land area estimates in Section 6.3 Land Converted to Forest Land (CRF Category 4A2) of this *Inventory* are compiled using NFI data. Forest Land area estimates obtained from these data are also used as part of Section 6.1 Representation of the U.S. Land Base (CRF Category 4.1). The land converted to forest land area estimates in Section 6.3 do not include Hawaii or the U.S. Territories as insufficient data is available from the NFI to compile area estimates of land use conversions over the entire time series. The National Land Cover Dataset is used in addition to NRI estimates in Section 6.1 Representation of the U.S. Land Base and land converted to forest land in Hawaii is included in that section, but the U.S. Territories are not included. Also, it is not possible to separate forest land remaining forest land from land converted to forest land in Wyoming because of the split annual cycle method used for population estimation; this prevents harmonization of forest land in Wyoming with the NRI/NLCD method used in Section 6.1 Representation of the U.S. Land Base (CRF Category 4.1). These issues result in small differences in the managed forest Land area in Sections 6.1 and 6.3 of this *Inventory* (Table A-212). There are also other factors contributing to the small differences in area such as harmonization of aspatial and spatial data across all land-use categories in Section 6.1 over the entire *Inventory* time series.

Table A-209: Annual change in Mineral Soil C stocks from U.S. agricultural soils that were estimated using a Tier 2 method (MMT C/year)

Category	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Cropland Converted to Forest Land	0.07 (0.04 to 0.11)	0.06 (0.02 to 0.09)	0.06 (0.02 to 0.1)	0.05 (0.02 to 0.09)	0.05 (0.01 to 0.08)	0.04 (0.01 to 0.07)	0.03 (0.01 to 0.06)	0.03 (0.01 to 0.05)	0.03 (-0.01 to 0.07)	0.03 (-0.01 to 0.07)
Grassland Converted to Forest Land	-0.04 (-0.08 to 0)	-0.04 (-0.08 to 0)	-0.05 (-0.1 to 0)	-0.06 (-0.11 to -0.01)	-0.06 (-0.11 to -0.01)	-0.06 (-0.11 to -0.01)	-0.05 (-0.1 to 0)	-0.05 (-0.1 to 0)	-0.05 (-0.13 to 0.02)	-0.05 (-0.13 to 0.02)
Other Lands Converted to Forest Land	0.13 (0.12 to 0.15)	0.15 (0.14 to 0.17)	0.17 (0.16 to 0.19)	0.20 (0.18 to 0.23)	0.22 (0.2 to 0.24)	0.26 (0.24 to 0.29)	0.25 (0.22 to 0.27)	0.25 (0.23 to 0.27)	0.25 (0.16 to 0.34)	0.25 (0.13 to 0.37)
Settlements Converted to Forest Land	0.01 (0.01 to 0.01)	0.01 (0.01 to 0.01)	0.01 (0.01 to 0.01)	0.01 (0.01 to 0.01)	0.01 (0.01 to 0.01)	0.02 (0.01 to 0.02)	0.02 (0.01 to 0.02)	0.02 (0.01 to 0.02)	0.02 (0.01 to 0.02)	0.02 (0.01 to 0.02)
Wetlands Converted to Forest Land	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)
Total Lands Converted to Forest Lands	0.17	0.17	0.19	0.21	0.22	0.26	0.24	0.24	0.24	0.24

Note: The range is a 95 percent confidence interval from 50,000 simulations (Ogle et al. 2003, 2006).

Table A-210: Annual change in Mineral Soil C stocks from Federal U.S. agricultural soils that were estimated using a Tier 2 method (MMT C/year)

Category	1990	1995	2000	2005	2010	2018	2019	2020	2021	2022
Cropland Converted to Forest Land	-0.02 (-0.04 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (-0.01 to 0.01)	0.00 (-0.02 to 0.02)
Grassland Converted to Forest Land	-0.01 (-0.02 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (-0.01 to 0.01)	0.00 (-0.02 to 0.02)
Other Lands Converted to Forest Land	0.07 (0.06 to 0.08)	0.01 (0 to 0.01)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.01 (-0.02 to 0.04)	0.01 (-0.04 to 0.05)
Settlements Converted to Forest Land	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)
Wetlands Converted to Forest Land	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)	0.00 (0 to 0)

Total Lands Converted to Forest Lands	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
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Note: The range is a 95 percent confidence interval from 50,000 simulations (Ogle et al. 2003, 2006).

Table A-211: Total land areas (hectares) by land use/land-use change subcategory for mineral soils between 1990 to 2022

Conversion Land Areas (Hectares x10⁶)	1990	1995	2000	2005	2014	2015	2016	2017	2018	2019	2020	2021	2022
Cropland Converted to Forest Land	0.21	0.14	0.16	0.14	0.12	0.12	0.11	0.11	0.10	0.09	0.08	0.08	0.08
Grassland Converted to Forest Land	0.76	0.91	0.96	0.95	1.00	0.99	0.96	0.95	0.93	0.94	0.93	0.93	0.94
Other Lands Converted to Forest Land	0.07	0.05	0.05	0.07	0.09	0.09	0.10	0.11	0.10	0.10	0.10	0.09	0.09
Settlements Converted to Forest Land	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Wetlands Converted to Forest Land	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01
Total Lands Converted to Forest Lands	1.06	1.14	1.20	1.19	1.24	1.23	1.21	1.20	1.17	1.16	1.14	1.13	1.13

Note: Estimated with a Tier 2 approach and based on analysis of USDA National Resources *Inventory* data (USDA-NRCS 2018).

Table A-212: Land Converted to Forest Land area estimates and differences between estimates in the Representation of the U.S. Land Base (CRT Category 4.1) and Land Converted to Forest Land (CRT Category 4A1) (kha)

Year	1990	1995	2000	2005	2010	2017	2018	2019	2020	2021	2022
Cropland Converted to Forest Land - 6.1 Representation of the U.S. Land Base (CRF Category 4.1)	208	144	158	137	128	107	101	88	77	77	76
Cropland Converted to Forest Land - 6.3 Land Converted to Forest Land (CRF Category 4A2)	157	156	156	153	153	160	159	158	154	155	155
Difference between estimates	51	(13)	1	(16)	(25)	(53)	(58)	(70)	(77)	(78)	(79)
Grassland Converted to Forest Land - 6.1 Representation of the U.S. Land Base (CRF Category 4.1)	775	924	971	968	1,024	1,055	1,038	1,048	1,036	1,037	1,040
Grassland Converted to Forest Land - 6.3 Land Converted to Forest Land (CRF Category 4A2)	665	698	687	678	726	730	728	728	723	724	724
Difference between estimates	109	226	283	290	298	325	310	320	313	313	316
Other Lands Converted to Forest Land - 6.1 Representation of the U.S. Land Base (CRF Category 4.1)	77	50	59	73	81	112	108	98	99	94	89
Other Lands Converted to Forest Land - 6.3 Land Converted to Forest Land (CRF Category 4A2)	32	32	32	32	33	33	33	33	33	33	33
Difference between estimates	45	18	26	41	48	79	75	65	67	61	56

Settlements Converted to Forest Land - 6.1 Representation of the U.S. Land Base (CRF Category 4.1)	11	19	18	18	18	20	20	21	20	19	20
Settlements Converted to Forest Land - 6.3 Land Converted to Forest Land (CRF Category 4A2)	170	169	168	165	168	172	171	171	166	167	167
Difference between estimates	(159)	(150)	(150)	(147)	(150)	(152)	(150)	(150)	(146)	(148)	(147)
Wetlands Converted to Forest Land - 6.1 Representation of the U.S. Land Base (CRF Category 4.1)	15	25	24	23	24	20	21	18	16	15	15
Wetlands Converted to Forest Land - 6.3 Land Converted to Forest Land (CRF Category 4A2)	51	53	53	52	52	53	53	54	53	54	54
Difference between estimates	(36)	(28)	(30)	(29)	(28)	(33)	(33)	(36)	(37)	(38)	(39)
Total	10	53	132	139	143	166	144	129	120	110	108

Uncertainty Analysis

The uncertainty analyses for total net flux of forest carbon (see Table 6-14 in the FLRFL section) are consistent with the IPCC-recommended Tier 1 methodology (IPCC 2006). Specifically, they are considered approach 1 (propagation of error [Section 3.2.3.1]) (IPCC 2006). To better understand the effects of covariance, the contributions of sampling error and modeling error were parsed out. In addition, separate analyses were produced for forest ecosystem and HWP flux.

Estimates of forest carbon stocks in the United States are based on carbon estimates assigned to each of several thousand inventory plots from a regular grid. Uncertainty in these estimates and uncertainty associated with change estimates arise from many sources including sampling error and modeling error. Here EPA focuses on these two types of error but acknowledge several other sources of error are present in the overall stock and stock change estimates. In terms of sampling-based uncertainty, design-based estimators described by Bechtold and Patterson (2005) were used to quantify the variance of carbon stock estimates. In this section EPA denotes the estimate of carbon stock at time t as C_t and the variances of the estimate of carbon stock for time t as $\text{Var}(C_t)$. These calculations follow Bechtold and Patterson (2005). The variance of stock change is then:

Equation A-62: Variance of the Carbon Stock Change

$$\text{Var}(C_{t2} - C_{t1}) = \text{Var}(C_{t2}) + \text{Var}(C_{t1}) - 2 \times \text{Cov}(C_{t2}, C_{t1}) \quad (15)$$

The uncertainty of a stock estimate associated with sampling error is $U(C_t)_s = \text{Var}(C_t)^{0.5}$. The uncertainty of a stock changes estimate associated with sampling error is $U(\Delta C)_s = \text{Var}(C_{t2} - C_{t1})^{0.5}$.

Model-based uncertainty is important because the pool-level carbon models have error. The total modeling mean-squared error (MSE_m) is approximately 1,622 (Mg/ha)². The percent modeling error at time t is

Equation A-63: Percent Modeling Error

$$\%U(C_t)_m = 100 \times \text{MSE}_m / dt \quad (16)$$

Where dt is the total carbon stock density at time t calculated as C_t / A_t where A_t is the forest area at time t .

The uncertainty of C_t from modeling error is

Equation A-64: Uncertainty of Carbon Stock Estimate at Time t

$$U(C_t)_m = C_t \times \%U(C_t)_m / 100 \quad (17)$$

The model-based uncertainty with respect to stock change is then

Equation A-65: Model-based Uncertainty of Carbon Stock Change

$$U(\Delta C)_m = (U(C_{t1})_m + U(C_{t2})_m - 2 \times \text{Cov}(U(C_{t1})_m, U(C_{t2})_m))^{0.5} \quad (18)$$

The sampling and model-based uncertainty are combined for an estimate of total uncertainty. We considered these sources of uncertainty independent and combined as follows for stock change (ΔC):

Equation A-66: Total Uncertainty of Carbon Stock Change

$$U(\Delta C) = (U(\Delta C)_m^2 + U(\Delta C)_s^2)^{0.5} \text{ and the 95 percent confidence bounds was } \pm 2 \times U(\Delta C) \quad (19)$$

The mean square error (MSE) of pool models was (MSE, [Mg C/ha]²): soil C (1143.0), litter (78.0), live tree (259.6), dead trees (101.5), understory (0.9), down dead wood (38.9), total MSE (1,621.9).

Numerous assumptions were adopted for creation of the forest ecosystem uncertainty estimates. Potential pool error correlations were ignored. Given the magnitude of the MSE for soil, including correlation among pool error would not appreciably change the modeling error contribution. Modeling error correlation between time 1 and time 2 was assumed to be 1. Because the MSE was fixed over time EPA assumed a linear relationship dependent on either the measurements at two points in time or an interpolation of measurements to arrive at annual flux estimates. Error associated with interpolation to arrive at annual flux is not included.

Uncertainty about net carbon flux in HWP is based on Skog et al. (2004) and Skog (2008). Latin hypercube sampling is the basis for the HWP Monte Carlo simulation. Estimates of the HWP variables and HWP Contribution under the production approach are subject to many sources of uncertainty. An estimate of uncertainty is provided that evaluated the effect of uncertainty in 13 sources, including production and trade data and parameters used to make the estimate. Uncertain

data and parameters include data on production and trade and factors to convert them to carbon, the census-based estimate of carbon in housing in 2001, the EPA estimate of wood and paper discarded to SWDS for 1990 to 2000, the limits on decay of wood and paper in SWDS, the decay rate (half-life) of wood and paper in SWDS, the proportion of products produced in the United States made with wood harvested in the United States, and the rate of storage of wood and paper carbon in other countries that came from U.S. harvest, compared to storage in the United States.

The uncertainty about HWP and forest ecosystem net carbon flux were combined and assumed to be additive. Typically, when propagating error from two estimates the variances of the estimates are additive. However, the uncertainty around the HWP flux was approximated using a Monte Carlo approach which resulted in the lack of a variance estimate for HWP carbon flux. Therefore, EPA considered the uncertainty additive between the HWP sequestration and the forest land remaining forest land sequestration. Further, EPA assumed there was no covariance between the two estimates which is plausible as the observations used to construct each estimate are independent.

Emissions from Forest Fires

CO₂ Emissions from Forest Fires

As stated in other sections, the forest inventory approach implicitly accounts for CO₂ emissions due to disturbances. Net carbon stock change is estimated from successive carbon stock estimates. A disturbance, such as a forest fire, removes carbon from the forest. The inventory data, on which net carbon stock estimates are based, already reflects the carbon loss from such disturbances because only carbon remaining in the forest is estimated. Estimating the CO₂ emissions from a disturbance such as fire and adding those emissions to the net CO₂ change in forests would result in double-counting the loss from fire because the inventory data already reflect the loss. There is interest, however, in the size of the CO₂, CH₄, and N₂O emissions from disturbances such as fire.

Estimates of historic forest fires and associated emissions (i.e., from 1990 through the current year) provided with this report are updated each year to represent any improvements in available data or methodology. Most of this year's estimates are based on a system of country-specific models and spatially defined burn areas to simulate fire emissions (i.e., for the 48 conterminous states and Alaska). However, emissions estimates for Hawaii, Puerto Rico, and Guam are based on spatially defined burn data with Tier-1 emissions factors (IPCC 2019), which represent updates of the IPCC (2006) guidance on reporting fire emissions.

Estimated annual emissions (CO₂ and non-CO₂) from forest fires over the interval from 1990 to the current inventory are calculated consistent with IPCC (2019) methodology, which is also updated relative to IPCC (2006); this includes U.S.-specific data and models on area, fuel, consumption, and emission. Area of forest burned is based on annual area of forest coincident with fires according to annual datasets from Monitoring Trends in Burn Severity (MTBS perimeters, Eidenshink et al. 2007), MODIS burned area mapping (MODIS MCD64A1 V6.1, Giglio et al. 2018), or Wildland Fire Interagency Geospatial Service interagency fire perimeters (WFIGS 2023). Annual forest fire and emissions estimates were calculated by the Wildland Fire Emissions *Inventory* System (WFEIS, French et al. 2011, 2014). The WFEIS calculator¹¹⁴ was used to provide annual emissions estimates by state and year for the MODIS-based burned areas and by individual fire events for the MTBS and WFIGS burned areas. Note that N₂O emissions are not included in WFEIS calculations; emissions provided here are based on the average N₂O to CO₂ ratio of 0.000166 (Larkin et al. 2014, IPCC 2019).

Forest areas within the full burn boundaries (MTBS, WFIGS, or MODIS) were based on two fuels layers within WFEIS – the Fuel Characteristic Classification System (FCCS, Prichard et al. 2019) and the North American Wildland Fuels Database (NAWFD, Prichard et al. 2019). Each delineates fuelbed classes, and forest classifications within each fire identified forest land per fire. Additionally, the National Land Cover (NLCD) images that include forest transition classes (Homer et al. 2015; Yang et al. 2018) identified forest land on the spatial burn features in order to compare with forest burned areas from the fuels models as a quality assurance step and to identify spatial subsets such as forests on managed land in Alaska or forests within specific states. The MTBS data do not include fires smaller than approximately 400 or 200 ha for the western or eastern United States, respectively. Fire areas and emissions reported for Alaska are reduced to only include managed land (Ogle et al. 2018); forest fires on managed land averaged 66 percent of total Alaska forest fires over the years 2012 through 2021.

¹¹⁴ See <https://wfeis.mtri.org/calculator>.

Emissions from prescribed fires on forest land contribute to total annual emissions from forest fires. However, information on area or emissions from prescribed fires on forest land is limited. Delineation of emissions associated with prescribed fires is not available in the WFEIS calculations as applied here. The MTBS and WFIGS records identify fire origin, including many prescribed fires. Based on MTBS fire origins, we estimate that an annual average of about 15 percent of forest land within the MTBS burn perimeters were prescribed forest burns over the 10-year interval 2011-2020 (based on NLCD land cover over MTBS perimeters in the conterminous United States + Alaska). In 2020, 8 percent of the MTBS forest fires were identified as prescribed. However, note that the minimum size thresholds for MTBS reporting are likely to exclude many of the smaller controlled burns.

Statistics for all prescribed fires, but without separate forest classification, are available for the U.S. The National Interagency Fire Center¹¹⁵ reports 2.45 million hectares of prescribed fires in 2019 and annual reports by the National Association of State Foresters and the Coalition of Prescribed Fire Councils¹¹⁶ report 4.05 million hectares of prescribed fires in 2019. In 2019, the most recent year with these prescribed burn data, 20.6 percent of MTBS forest fires (also based on forest cover as described above) were labeled as prescribed; however, also note that the WFEIS-calculated total forest area burned was 0.78 million hectares (and 20.6 percent of this is 0.16 million hectares).

The MTBS data available for this report (MTBS 2023) included fires from 1990 through 2021 for all states and Puerto Rico (the exception was Alaska 2021 where emissions calculations were not available). The MODIS-based records include 2001 through 2022 for the 48 conterminous states plus Alaska. The WFIGS-based records for 2020 through 2022 included all states plus Puerto Rico and Guam. All emissions calculations were based on these burned area definitions. The WFEIS calculator provided all other parts of calculations—fuels, fire characteristics, and emissions—for the conterminous states and Alaska. The burn perimeters for Hawaii, Puerto Rico and Guam were partly allocated to forest land according to forest cover (Homer et al. 2015), with fuels, consumption, and emissions estimates made according to Tier-1 factors for secondary tropical forests (IPCC 2019).

Current uncertainty estimates provided with emissions are based on variability among the limited alternate mean estimates per state per year. That is, the three burn sources and the two fuel models can produce multiple estimates, depending on year. Two annual estimates for 1990 through 2000 are MTBS-based while estimates for subsequent years depend on availability of burned area information. Uncertainty in the MTBS or MODIS data are not currently addressed. Similarly, uncertainty in other parts of the WFEIS system, such as the Consume model (Prichard et al. 2014), are not a part of the uncertainty quantified here. Planned improvements for future analyses are to incorporate preliminary WFEIS uncertainty analyses (Prichard et al. 2019; Kennedy et al. 2020) in reported forest fire emissions. Variability in fuel loading modeled from use of the NAWFD data is available through additional calculation and download of the WFEIS calculator¹¹⁷ as emissions based on the 25th, 50th, or 75th percentiles of fuel. These data were considered for developing uncertainty, but their use was inconsistent with the single mean values from FCCS, but the quantiles may be incorporated in future analyses. A simple Monte Carlo (Approach 2) method was employed to propagate uncertainty by state by year to country-wide totals. For additional details and analysis see Smith et al. (in preparation).

¹¹⁵ See <https://www.nifc.gov/fire-information/statistics>.

¹¹⁶ See <http://www.prescribedfire.net/>.

¹¹⁷ See <https://wfeis.mtri.org/calculator>.

Table A-213: Areas (Hectares) and Corresponding Emissions (MMT/year) Associated with Past Forest Fires^a

		1990	1995	2000	2005	2010	2015	2019	2020	2021	2022
Conterminous States (48), Hawaii, Puerto Rico, and Guam	Forest area burned (1000 ha)	114.5	101.0	680.2	352.2	327.8	801.0	276.7	1053.8	1339.6	729.3
	C emitted (MMT/yr)	3.7	2.6	21.3	8.8	7.0	26.1	5.9	38.3	48.4	22.2
	CO ₂ emitted (MMT/yr)	11.9	8.4	69.0	28.6	23.0	84.6	19.1	124.0	156.7	71.8
Alaska	Forest area burned (1000 ha)	275.4	5.7	74.5	620.4	39.2	637.2	215.1	4.0	43.1	363.7
	C emitted (MMT/yr)	13.3	0.3	4.1	35.1	2.1	37.5	10.5	0.1	2.1	17.7
	CO ₂ emitted (MMT/yr)	43.2	1.0	13.2	113.5	6.9	121.3	34.0	0.4	6.8	57.4
Conterminous States (48), Alaska, Hawaii, Puerto Rico, and Guam	CH ₄ emitted (kt/yr)	122.0	20.2	219.5	327.9	63.2	509.9	120.2	349.4	452.2	326.7
	N ₂ O emitted (kt/yr)	9.1	1.6	13.6	23.6	5.0	34.2	8.8	20.7	27.1	21.5
	CO emitted (kt/yr)	3179.1	490.6	4845.3	8447.2	1628.8	12273.4	3054.1	7265.9	9597.9	7593.0
	NO _x emitted (kt/yr)	48.8	11.5	78.4	123.5	34.9	181.7	50.5	123.1	159.8	121.3

^a These emissions have already been accounted for in the estimates of net annual changes in carbon stocks, which accounts for the amount sequestered minus any emissions, including the assumption that combusted wood may continue to decay through time.

Table A-214: Equivalence Ratios, of CH₄ and N₂O to CO₂-equivalent

Equivalence Ratios ^{a,b}	
CH ₄ to CO _{2eq}	28
N ₂ O to CO _{2eq}	265

^a Source: the IPCC *Fifth Assessment Report* (2013)

^b Note that the corresponding past values for the equivalence ratios from the IPCC *Fourth Assessment Report* are 25 and 298 for CH₄ and N₂O, respectively (for example, see IPCC 2007).

Non-CO₂ Emissions from Forest Fires

Emissions of non-CO₂ gases (CH₄, N₂O, CO, and NO_x) (Table A-214) are estimated using the same WFEIS calculator approach as described above for estimating CO₂ emissions from forest fires. Values for global warming potential (GWP) to express CH₄ and N₂O as CO₂ equivalents (Table A-213) are based on the IPCC *Fifth Assessment Report* (IPCC 2013) Estimated uncertainty follows methods described in the previous section.

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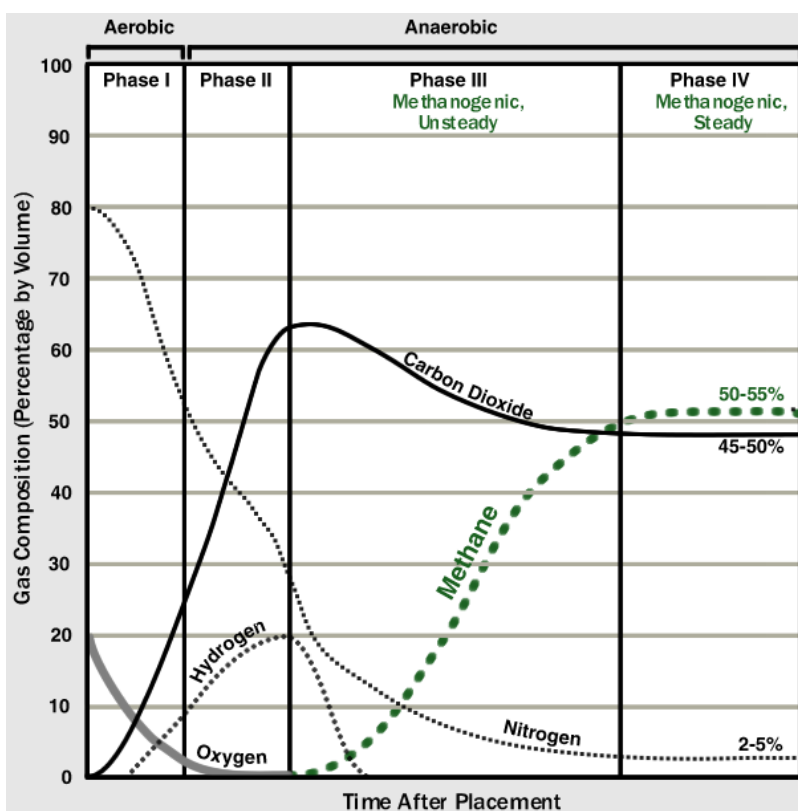
3.14. Methodology for Estimating CH₄ Emissions from Landfills

A combination of Tier 2 and 3 approaches are used to calculate emissions from MSW Landfills. A Tier 2 approach is used to calculate emissions for industrial waste landfills.

Landfill gas is a mixture of substances generated when bacteria decompose the organic materials contained in solid waste. By volume, landfill gas is about half CH₄ and half CO₂.¹⁷² The amount and rate of CH₄ generation depends upon the quantity and composition of the landfilled material, as well as the surrounding landfill environment. Not all CH₄ generated within a landfill is emitted to the atmosphere. The CH₄ can be extracted and either flared or utilized for energy, thus oxidizing the CH₄ to CO₂ during combustion. Of the remaining CH₄, a portion oxidizes to CO₂ as it travels through the top layer of the landfill cover. In general, landfill-related CO₂ emissions are of biogenic origin and primarily result from the decomposition, either aerobic or anaerobic, of organic matter such as food or yard wastes.

Figure A-20 illustrates how landfill gas composition varies over time after waste is disposed in an MSW landfill when bacterial populations decompose the waste in different, often concurrent phases of waste decomposition (ATSDR 2001). Gas is generated at a stable rate in Phase IV for approximately 20 years and may be generated for 50 or more years after waste is placed in the landfill depending on management practices and waste composition (ASTDR 2001).

Figure A-20: Landfill Gas Composition Over Time



Source: ASTDR (2001)

Methane emissions from landfills are estimated using two primary methods. The first method uses the first order decay (FOD) model as described by the 2006 IPCC Guidelines to estimate CH₄ generation. The amount of CH₄ recovered and combusted from MSW landfills is subtracted from the CH₄ generation and is then adjusted with an oxidation factor. The second method used to calculate CH₄ emissions from landfills, also called the back-calculation method, is based off

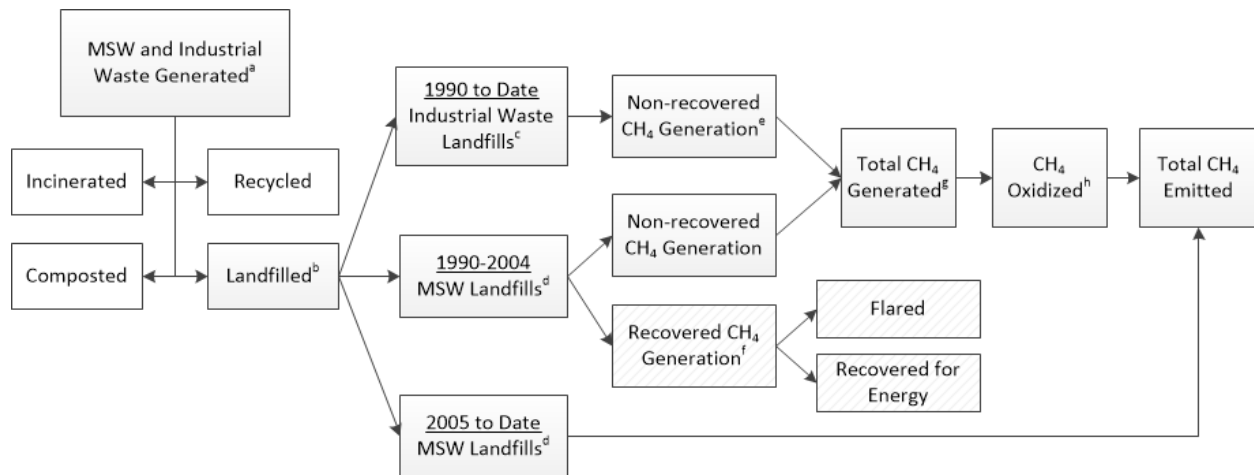
¹⁷² Typically, landfill gas also contains small amounts of nitrogen, oxygen, and hydrogen, less than 1 percent nonmethane volatile organic compounds (NMVOCs), and trace amounts of inorganic compounds.

directly measured amounts of recovered CH₄ from the landfill gas and is expressed by Equation HH-8 in CFR Part 98.343 of the EPA's Greenhouse Gas Reporting Program (GHGRP).

The current *Inventory* methodology uses both methods to estimate CH₄ emissions across the time series. The 1990 to 2015 *Inventory* was the first *Inventory* to incorporate directly reported GHGRP net CH₄ emissions data for landfills. In previous *Inventories*, only the first order decay method was used. EPA's GHGRP requires landfills meeting or exceeding a threshold of 25,000 metric tons (MT) of CH₄ generation per year to report a variety of facility-specific information, including historical and current waste disposal quantities by year, CH₄ generation, gas collection system details, CH₄ recovery, and CH₄ emissions. EPA's GHGRP provides a consistent methodology, a broader range of values for the oxidation factor, and allows for facility-specific annual waste disposal data to be used, thus these data are considered Tier 3 (highest quality data) under the *2006 IPCC Guidelines*. Using EPA's GHGRP data was a significant methodological change and required a merging of the GHGRP methodology with the *Inventory* methodology used in previous years to ensure time-series consistency.

Figure A-21 presents the CH₄ emissions process—from waste generation to emissions—in graphical format. A detailed discussion of the steps taken to compile the 1990 to 2022 *Inventory* are presented in the remainder of this Annex.

Figure A-21: Methane Emissions Resulting from Landfilling Municipal and Industrial Waste



^a MSW waste generation is not calculated because annual quantities of waste landfilled are available through secondary sources as described in figure note b.

^b Quantities of MSW landfilled for 1940 through 1988 are based on EPA 1988 and EPA 1993; 1989 through 2004 are based on *BioCycle* 2010; 2005 through 2022 are incorporated through the directly reported emissions from MSW landfills to the Greenhouse Gas Reporting Program. Quantities of industrial waste landfilled are estimated using a disposal factor and industrial production data sourced from Lockwood Post's Directory and the USDA.

^c The *2006 IPCC Guidelines* – First Order Decay (FOD) Model is used for industrial waste landfills.

^d Two different methodologies are used in the time series for MSW landfills. For 1990 to 2004, the *2006 IPCC Guidelines* – FOD Model is used. For 2005 to 2022, directly reported net CH₄ emissions from the GHGRP for 2010 to the current *Inventory* year are used with the addition of a scale-up factor applied to each year's emissions. The scale-up factor accounts for emissions from landfills that do not report to the GHGRP. A scale-up factor of 9 percent is applied to 2005-2016 and a scale-up factor of 11 percent is applied to 2017-2022. The GHGRP emissions from 2010 to the current *Inventory* year are also used to backcast emissions for 2005 to 2009 to merge the FOD methodology with the GHGRP methodology for time series consistency. Additional details on how the scale-up factor was developed and the backcasting approach are included in Step 4 of this Annex chapter.

^e Methane recovery from industrial waste landfills is not incorporated into the *Inventory* because it does not appear to be a common practice according to the GHGRP dataset.

^f Methane recovery data are pulled from four recovery databases: EIA 2007, flare vendor database, the landfill gas-to-energy database, and EPA (GHGRP) 2015(a). These databases are used to estimate national recovery for the *Inventory* between 1990 to 2009. CH₄ recovery estimates between 2010 to the current inventory year are calculated from GHGRP recovery amounts with a scale-up factor applied as explained in Step 3 of this Annex chapter.

^g For years 1990 to 2004, the total CH₄ generated from MSW landfills and industrial waste landfills are summed. For years 2005 to 2022, MSW landfill CH₄ generated is back-calculated from the annual net CH₄ emissions, recovery, and oxidation; CH₄ generation from industrial waste landfills are summed with the back-calculated MSW landfills CH₄ generation amounts.

^h An oxidation factor of 10 percent is applied to all CH₄ generated in years 1990 to 2004 (*2006 IPCC Guidelines*; Mancinelli and McKay 1985; Czepiel et al 1996). For 2005 to 2022, directly reported CH₄ emissions from the GHGRP are used for MSW landfills. Various oxidation factor percentages are included in the GHGRP dataset (0, 10, 25, and 35); an average percent of 0.14 is effectively applied between 2005 to 2009, 0.17 between 2010 to 2014, 0.20 between 2015 to 2019, 0.22 between 2020 to 2021, and 0.23 applied for 2022.

Step 1: Estimate Annual Quantities of Solid Waste Placed in MSW Landfills for 1940 to the Present Year

Total national annual waste generation and disposal data back to 1940 are directly used to estimate CH₄ emissions for the 1990 to 2009 *Inventory* time series. The waste generation and disposal estimates are also made for the rest of the *Inventory* time series (i.e., 2010 to the current *Inventory* year) for informational purposes; these data however do not inform the annual CH₄ emission estimates for this portion of the time series. The specific steps are described below (in sections 1a and 1b), followed by a summary of a comparative analysis of datasets that contain or are used to estimate annual waste disposal (in Box A-3). Step 2 describes how the estimated annual quantities of waste landfilled are used to estimate annual CH₄ generation between 1990 to 2009, and the methodology used to estimate CH₄ generation for 2010 to the current *Inventory* year.

Step 1a. Historical Estimates: 1940 to 1988

Historical waste data, preferably from 50 years prior to the first year of the *Inventory* time series (i.e., since 1940 because the time series begins in 1990), are required for the FOD model to estimate CH₄ generation for the *Inventory* time series (IPCC 2006). States and local municipalities across the United States do not consistently track and report quantities of MSW generated or collected for management, nor do they report end-of-life disposal methods to a centralized system. Therefore, national MSW landfill waste generation and disposal data are obtained from secondary data sources or estimated via proxy data.

Estimates of the annual quantity of waste landfilled for 1960 through 1988 were obtained from EPA's Anthropogenic Methane Emissions in the United States, Estimates for 1990: Report to Congress (EPA 1993) and an extensive landfill survey by the EPA's Office of Solid Waste in 1986 (EPA 1988). Although waste placed in landfills in the 1940s and 1950s contributes very little to current CH₄ generation, estimates for those years were included in the FOD model for completeness in accounting for CH₄ generation rates and are based on the population in those years and the per capita rate for land disposal for the 1960s.

Step 1b. Inventory Time Series Estimates: 1990 to the Current Inventory Year

For 1989 to 2008, estimates of the annual quantity of MSW generated were developed from a survey of state agencies as reported in the State of Garbage (SOG) in America surveys (BioCycle 2001, 2004, 2006, 2010), adjusted to include U.S. Territories.¹⁷³ The SOG surveys collected data from state agencies and then applied the principles of mass balance where all MSW generated is equal to the amount of MSW landfilled, combusted in waste-to-energy plants, composted, and/or recycled (BioCycle 2006; Shin 2014). This approach assumes that all waste management methods are tracked and reported to state agencies. Survey respondents were asked to provide a breakdown of MSW generated and managed by landfilling, recycling, composting, and combustion (in waste-to-energy facilities) in actual tonnages as opposed to reporting a percent generated under each waste disposal option. The data reported through the surveys have typically been adjusted to exclude non-MSW materials (e.g., industrial and agricultural wastes, construction and demolition debris, automobile scrap, and sludge from wastewater treatment plants) that may be included in survey responses. While non-municipal solid wastes may have been disposed of in MSW landfills, they were not the primary type of waste material disposed and are typically inert. In last survey (BioCycle 2010), state agencies were asked to provide MSW-only data. Where this was not possible, they were asked to provide comments to better understand the data being reported. Methodological changes have occurred over the time frame the SOG surveys have been published, which directly

¹⁷³ Since the SOG survey does not include U.S. Territories, waste landfilled in U.S. Territories was estimated using population data for the U.S. Territories (U.S. Census Bureau 2020 and 2022) and the per capita rate for waste landfilled from BioCycle (2010).

impacted the fluctuating trends observed in the waste disposal data and emission estimates from 1990 to 2004 (RTI 2013).

The SOG survey is voluntary and not all states provided data in each survey year. To estimate waste generation for states that did not provide data in any given reporting year, one of the following methods was used (RTI 2013):

- For years when a state-specific waste generation rate was available from the previous SOG reporting year submission, the state-specific waste generation rate for that state was used. – or –
- For years where a state-specific waste generation rate was not available from the previous SOG reporting year submission, the waste amount is generated using the national average waste generation rate. In other words, Waste Generated = Reporting Year U.S. Population × the National Average Waste Generation Rate
 - The National Average Waste Generation Rate is determined by dividing the total reported waste generated across the reporting states by the total population for reporting states.
 - This waste generation rate may be above or below the waste generation rate for the non-reporting states and contributes to the overall uncertainty of the annual total waste generation amounts used in the model.

Use of these methods to estimate solid waste generated by states is a key aspect of how the SOG data was manipulated and why the results differ for total solid waste generated as presented in the SOG reports and in the *Inventory*. In the early years (2002 data in particular), SOG made no attempt to fill gaps for non-survey responses. For the 2004 data, the SOG team used proxy data (mainly from the Waste Business Journal [WBJ]) to fill gaps for non-reporting states and survey responses.

Although some fluctuation in waste generation data reported by states to the SOG survey is expected, for some states, the year-to-year fluctuations are quite significant (>20 percent increase or decrease in some case) (RTI 2013). The SOG survey reports for these years do not provide additional explanation for these fluctuations and the source data are not available for further assessment. Although exact reasons for the large fluctuations are difficult to obtain without direct communication with states, staff from the SOG team that were contacted speculated that significant fluctuations are present because the particular state could not gather complete information for waste generation (i.e., they are missing part of recycled and composted waste data) during a given reporting year. In addition, SOG team staff speculated that some states may have included C&D and industrial wastes in their previous MSW generation submissions but made efforts to exclude that (and other non-MSW categories) in more recent reports (RTI 2013).

The SOG surveys provide state-specific landfill waste generation data used in the *Inventory* for select years – 1989 to 2000, 2002, 2004, 2006, and 2008. In-between year waste generation is interpolated using the prior and next SOG report data. For example, waste generated in 2003 = (waste generation in 2002 + waste generation in 2004)/2.

For the *Inventory* year 2010 and later, EREF's 2016 report entitled, *MSW Management in the United States*, is used as the primary data source because BioCycle ceased preparing the SOG surveys. EREF (2016) includes state-specific landfill MSW generation and disposal data for 2010 and 2013 using a similar methodology as the SOG surveys. Waste generation data were interpolated for 2009, the year in-between the 2008 SOG survey data and the 2010 EREF data. Waste generation data were also extrapolated for 2011 and 2012 using the EREF data for 2010 and 2013. Waste generation data for 2014 and the current year were extrapolated based on the EREF 2013 data and population increases from the U.S. Census (U.S. Census Bureau 2020, 2022, and 2023). No data source on annual waste generation by state or nationally (similar to an SOG or EREF report) has been published since EREF (2016).

For each year in the time series, estimates of the quantity of waste landfilled are determined by applying a waste disposal factor to the total amount of waste generated. A waste disposal factor was determined for each year a SOG survey was published and is the ratio of the total amount of waste landfilled to the total amount of waste generated. The waste disposal factor is interpolated for the years in between the SOG surveys and EREF report and extrapolated for years after the last year of EREF data (i.e., 2013). The applied waste disposal factor has ranged from approximately 77 percent in 1990 to 65.3 percent from 2015 to 2022.

Table A-215 shows estimates of MSW generated and landfilled, and industrial waste landfilled. A description of the data sources used to estimate industrial waste landfilled is included in Step 7. Estimates for MSW generated and landfilled are presented for various years after 2004 for informational purposes only. As described in Step 4, after 2004, the *Inventory* methodology relies on the GHGRP net reported CH₄ emissions data, replacing the need for the now discontinued SOG surveys and intermittent EREF estimates.

Table A-215: Solid Waste in MSW and Industrial Waste Landfills Contributing to CH₄ Emissions (MMT unless otherwise noted)

	1990	2005	2018	2019	2020	2021	2022
Total MSW Generated ^a	270	368	329	331	334	334	335
Percent of MSW Landfilled	77%	64%	65%	65%	65%	65%	65%
Total MSW Landfilled	205	234	213	214	216	216	217
MSW last 30 years ^b	4,876	5,992	6,520	6,537	6,548	6,559	6,582
MSW since 1940 ^c	6,808	9,925	12,721	12,935	13,150	13,366	13,583
Total Industrial Waste Production							
Data	198	223	212	209	205	204	202
Pulp and Paper Sector ^d	129	139	124	120	117	117	115
Food and Beverage Sector ^e	69	84	88	89	88	87	86
Percent Total Industrial Waste							
Landfilled	5%	5%	5%	5%	5%	5%	5%
Total Industrial Waste Landfilled	9.7	10.9	11.5	11.3	11.1	11.1	11.0
Pulp and Paper Sector ^d	6.5	6.9	6.2	6.0	5.9	5.9	5.8
Food and Beverage Sector ^e	3.3	4.0	5.3	5.3	5.3	5.2	5.2

^a This estimate represents the waste that has been in place for 30 years or less, which contributes about 90 percent of the CH₄ generation. Values are based on EPA (1993) for years 1940 to years 1988 (not presented in table), BioCycle 2001, 2004, 2006, and 2010 for years 1989 to 2009 (1981 to 2004, and 2006 to 2011 are not presented in table). Values for years 2010 to 2022 are based on EREF (2016) and annual population data from the U.S. Census Bureau (2020, 2022, and 2023).

^b This estimate is the cumulative amount of waste that has been placed in landfills for the 30 years prior to the year indicated and is the sum of the annual disposal rates used in the first order decay model. Values are based on EPA 1993; BioCycle 2001, 2004, 2006, and 2010; EREF 2016; and extrapolated data based on annual population increases (U.S. Census Bureau 2020, 2022, and 2023).

^c This estimate represents the cumulative amount of waste that has been placed in landfills since 1940 to the year indicated and is the sum of the annual disposal rates used in the first order decay model. Values are based on EPA 1993; BioCycle 2001, 2004, 2006, and 2010; EREF 2016; and extrapolated data based on annual population increases (U.S. Census Bureau 2020, 2022, and 2023).

^d A disposal factor of 0.050 MT/MT of product is applied to total pulp and paper production data to estimate the annual amount landfilled. See Step 7 for the references and rationale for this method. The same disposal factor is applied to every year of the time series. Production data from 1990 and 2001 are from Lockwood-Post's Directory (2002). Production data from 2002 to 2022 are from the FAOStat database.¹⁷⁴

^e A disposal factor of 0.0486 MT/MT of product is applied to total food production data to estimate the annual amount landfilled for years 1990 to 2009. A disposal factor of 0.060 MT/MT is applied for years 2010 to present. See Step 7 for the references and rationale for this method. Food production values for 1990 to 2022 are from FAO (2023).¹⁷⁵

Notes: Totals may not sum due to independent rounding.

Box A-3: Comparison of Annual Waste Disposal Estimates Across Available Data Sources

In 2020, EPA compared the available data on estimates of total waste generated and landfilled as presented in Table A-215 for the years 2017 and 2018 and found inconsistencies between the estimates of MSW landfilled between the data sources. Data sources directly compared include the EREF-extrapolated estimate for 2017 and 2018 to the Advancing Sustainable Materials Management: Facts and Figures report (EPA (2020) Advancing Sustainable Materials Management: Facts and Figures 2018, November 2020). These inconsistencies are expected, as the data sources use two different methodologies to estimate MSW landfilled. While there are differences in the methods used between these data sources, the uncertainty factors for MSW Landfills are intended to account for these variabilities in the emission estimates for 1990 to 2004.

The EREF-extrapolated national estimate of total MSW landfilled for 2017 and 2018 is based on a bottom-up approach using information at the facility-level to estimate national MSW for the sector as a whole, while the Facts and Figures report uses a top-down (materials flow mass balance) approach to estimate the same quantity. The materials flow methodology develops post-consumer MSW generation estimates of quantities of MSW products in the marketplace (using product sales and replacement data) and assessing waste generation by component material based on product

¹⁷⁴ Available at: <http://faostat3.fao.org/home/index.html#DOWNLOAD>. Accessed on September 5, 2023.

¹⁷⁵ 2022 USDA-NASS Ag QuickStats. Available at: <http://quickstats.nass.usda.gov>.

lifespans. Discarded or landfilled material is post-consumer MSW and assumed to be the calculated difference between generation and recovery through recycling and composting, other food management (e.g., anaerobic digestion), and combustion (EPA 2020). MSW typically does not include construction and demolition waste, for example, which many GHGRP-reporting facilities accept and include in their greenhouse gas reports.

As a quality check, EPA also compared the MSW landfilled estimates from the EREF-extrapolated data, the Facts and Figures report, and the estimated waste disposed by facilities reporting to EPA's GHGRP under Subpart HH (MSW Landfills) for 2017 and 2018 plus an 11 percent scale-up factor to account for landfills that do not report to Subpart HH.

On average, the EREF-extrapolated value was 39 percent less than GHGRP-based estimated waste disposal amount for the year 2017 and 41 percent less than GHGRP-based estimated waste disposal amount for the year 2018 (including a scale-up factor of 11 percent for 2017 and 2018).

The difference between the EREF-extrapolated and GHGRP-based estimates are largely assumed to be due to the difference in estimated number of facilities included in the respective sources, and because the EREF 2013 waste landfilled estimate was extrapolated to 2018 based on population growth. In 2013, EREF estimated 1,540 landfills (data collected from state agencies, individual facilities for Hawaii and Florida, and estimated using population-based estimates for Alaska, Idaho and Wyoming). In 2018, the GHGRP-based estimate includes 2,111 total facilities, including 1,136 facilities reporting to the GHGRP, and 975 assumed or confirmed operational MSW landfills identified through WBJ 2016 and LMOP 2020 that do not report to the GHGRP.

Estimates of MSW landfilled from the Facts and Figures report for the year 2017 and 2018 were, on average, 61 percent less than the GHGRP + scale-up factor waste quantity (including a scale-up factor of 11 percent and subtracting 23 percent estimate of construction and demolition waste for both years).

While this 61 percent difference is large, it is not unexpected given the Facts and Figures top-down mass balance methodology and focus on MSW (i.e., non-MSW streams are purposely excluded). The GHGRP uses a facility-specific, bottom-up approach to estimating emissions while the Facts and Figures report uses a top-down approach which incorporates many assumptions regarding production, import and export values, and estimated product life are built into the MSW generation and landfill disposal estimate at the national level. The Facts and Figures report also specifically omits certain types of waste that are explicitly included in the GHGRP reports, such as construction and demolition waste, industrial waste, biosolids (sludges), agricultural waste, and other inert wastes (EPA 2020). Construction and demolition waste that was reported under the GHGRP were excluded to the extent possible, but because the GHGRP facilities typically report a default waste composition, some construction and demolition waste may still be included in what is assumed to be the MSW quantity. Additionally, the amount of biosolids (sludges) and other non-MSW streams could not reliably be estimated and excluded from the GHGRP data and may also be contributing to the percent difference.

Step 2: Estimate CH₄ Generation at MSW Landfills

Step 2a. CH₄ Generation at MSW Landfills for 1990 to 2009

The FOD method is exclusively used for 1990 to 2009. For the FOD method, methane generation is based on nationwide MSW generation data, to which a national average disposal factor is applied; it is not landfill-specific.

The FOD method is presented below and is similar to Equation HH-6 in CFR Part 98.343 for MSW landfills, and Equation TT-6 in CFR Part 98.463 for industrial waste landfills.

Equation A-67: Net Methane Emissions from Solid Waste

$$\text{CH}_{4,\text{Solid Waste}} = [\text{G}_{\text{CH}_4,\text{MSW}} - \text{R}] - \text{Ox}$$

where,

$\text{CH}_{4,\text{Solid Waste}}$	=	Net CH ₄ emissions from solid waste
$\text{G}_{\text{CH}_4,\text{MSW}}$	=	CH ₄ generation from MSW or industrial waste landfills
R	=	CH ₄ recovered and combusted
Ox	=	CH ₄ oxidized from MSW or industrial waste landfills before release to the atmosphere

The input parameters needed for the FOD model equations are the mass of waste disposed each year (discussed under Step 1), degradable organic carbon (DOC) as a function of methane generation potential (L_0), and the decay rate constant (k). The equation below provides additional detail on the activity data and emission factors used in the $\text{CH}_{4,\text{MSW}}$ equation presented above to calculate CH₄ generation.

Equation A-68: Methane Generation from MSW Landfills

$$\text{CH}_{4,\text{MSW}} = \left[\sum_{x=S}^{T-1} \left\{ W_x \times L_0 \times \frac{16}{12} \times (e^{-k(T-x-1)} - e^{-k(T-x)}) \right\} \right]$$

where,

$\text{CH}_{4,\text{MSW}}$	=	Total CH ₄ generated from MSW or industrial waste landfills
T	=	Reporting year for which emissions are calculated
x	=	Year in which waste was disposed
S	=	Start year of calculation
W_x	=	Quantity of waste disposed of in the landfill in a given year
L_0	=	Methane generation potential (100 m ³ CH ₄ /Mg waste; EPA 1998, 2008)
16/12	=	conversion factor from CH ₄ to C
k	=	Decay rate constant (yr ⁻¹ , see Table A-216)

The DOC is determined from the CH₄ generation potential (L_0 in m³ CH₄/Mg waste) as shown in the following equation:

Equation A-69: Degradable Organic Carbon Fraction of Solid Waste

$$\text{DOC} = [L_0 \times 6.74 \times 10^{-4}] \div [F \times \frac{16}{12} \times \text{DOC}_f \times \text{MCF}]$$

where,

DOC	=	degradable organic carbon (fraction, kt C/kt waste),
L_0	=	CH ₄ generation potential (100 m ³ CH ₄ /Mg waste; EPA 1998, 2008),
6.74×10^{-4}	=	CH ₄ density (Mg/m ³),
F	=	fraction of CH ₄ by volume in generated landfill gas (equal to 0.5)
16/12	=	molecular weight ratio CH ₄ /C,
DOC_f	=	fraction of DOC that can decompose in the anaerobic conditions in the landfill (fraction equal to 0.5 for MSW), and
MCF	=	methane correction factor for year of disposal (fraction equal to 1 for anaerobic managed sites).

DOC values can be derived for individual landfills if a good understanding of the waste composition over time is known. A default DOC value is used in the *Inventory* because waste composition data are not regularly collected for all landfills nationwide. When estimating CH₄ generation for the years 1990 to 2009, a default DOC value is used. This DOC value is calculated from a national CH₄ generation potential¹⁷⁶ of 100 m³ CH₄/Mg waste (EPA 2008) as described below.

¹⁷⁶ Methane generation potential (L_0) varies with the amount of organic content of the waste material. A higher L_0 occurs with a higher content of organic waste.

The DOC value used in the CH₄ generation estimates from MSW landfills for 1990 to 2009 is 0.2028, which is based on the CH₄ generation potential of 100 m³ CH₄/Mg waste (EPA 1998; EPA 2008). After EPA developed the L₀ value, RTI analyzed data from a set of 52 representative landfills across the United States in different precipitation ranges to evaluate L₀, and ultimately the national DOC value. The 2004 Chartwell Municipal Solid Waste Facility Directory confirmed that each of the 52 landfills chosen accepted or accepts both MSW and construction and demolition (C&D) waste (Chartwell 2004; RTI 2009). The values for L₀ were evaluated from landfill gas recovery data for this set of 52 landfills, which resulted in a best fit value for L₀ of 99 m³/Mg of waste (RTI 2004). This value compares favorably with a range of 50 to 162 (midrange of 106) m³/Mg presented by Peer, Thorneloe, and Epperson (1993); a range of 87 to 91 m³/Mg from a detailed analysis of 18 landfills sponsored by the Solid Waste Association of North America (SWANA 1998); and a value of 100 m³/Mg recommended in EPA's compilation of emission factors (EPA 1998; EPA 2008; based on data from 21 landfills). Based on the results from these studies, a value of 100 m³/Mg appears to be a reasonable best estimate to use in the FOD model for the national inventory for years 1990 through 2009, and is the value used to derive the DOC value of 0.2028.

In 2004, the FOD model was also applied to the gas recovery data for the 52 landfills to calculate a decay rate constant (k) directly for L₀ = 100 m³/Mg. The decay rate constant was found to increase with annual average precipitation; consequently, average values of k were developed for three precipitation ranges, shown in Table A-216 and recommended in EPA's compilation of emission factors (EPA 2008).

Table A-216: Average Values for Rate Constant (k) by Precipitation Range (yr⁻¹)

Precipitation range (inches/year)	k (yr ⁻¹)
<20	0.020
20-40	0.038
>40	0.057

These values for k show reasonable agreement with the results of other studies. For example, EPA's compilation of emission factors (EPA 1998; EPA 2008) recommends a value of 0.02 yr⁻¹ for arid areas (less than 25 inches/year of precipitation) and 0.04 yr⁻¹ for non-arid areas. The SWANA (1998) study of 18 landfills reported a range in values of k from 0.03 to 0.06 yr⁻¹ based on CH₄ recovery data collected generally in the time frame of 1986 to 1995.

Using data collected primarily for the year 2000, the distribution of waste-in-place versus precipitation was developed from over 400 landfills (RTI 2004). A distribution was also developed for population versus precipitation for comparison. The two distributions were very similar and indicated that population in areas or regions with a given precipitation range was a reasonable proxy for waste landfilled in regions with the same range of precipitation. Using U.S. Census data and rainfall data, the distributions of population versus rainfall were developed for each Census decade from 1950 through 2010. The distributions showed that the U.S. population has shifted to more arid areas over the past several decades. Consequently, the population distribution was used to apportion the waste landfilled in each decade according to the precipitation ranges developed for k, as shown in Table A-217.

Table A-217: Percent of U.S. Population within Precipitation Ranges by Decade (%)

Precipitation Range (inches/year)	1950	1960	1970	1980	1990	2000
<20	10	13	14	16	19	20
20-40	40	39	37	36	34	33
>40	50	48	48	48	48	48

Note: The precipitation range data are no longer used in the IPCC waste model (i.e., the FOD method) for 2010 and later years. Totals may not add to 100% due to independent rounding.

Source: Years 1950 through 2000 are from RTI (2004) using population data from the U.S. Census Bureau and precipitation data from the National Climatic Data Center's National Oceanic and Atmospheric Administration.

The 2006 IPCC Guidelines also require annual proportions of waste disposed of in managed landfills versus unmanaged and uncategorized sites prior to 1980. Based on the historical data presented by Mintz et al. (2003), a timeline was developed for the transition from the use of unmanaged and uncategorized sites for solid waste disposed to the use of managed landfills. Based on this timeline, it was estimated that 6 percent of the waste that was land disposed in 1940 was disposed of in managed landfills and 94 percent was managed in uncategorized sites. The uncategorized sites represent those sites where not enough information was available to assign a percentage to unmanaged shallow versus unmanaged deep solid waste disposal sites. Between 1940 and 1980, the fraction of waste that was land disposed

transitioned towards managed landfills until 100 percent of the waste was disposed of in managed landfills in 1980. For wastes disposed of in the uncategorized sites, a methane correction factor (MCF) of 0.6 was used based on the recommended IPCC default value for uncharacterized land disposal (IPCC 2006). The recommended IPCC default value for the MCF for managed landfills of 1 (IPCC 2006) has been used for the managed landfills for the years where the first order decay methodology was used (i.e., 1990 to 2009).

Step 2b. CH₄ Generation at MSW Landfills for 2010 to Present

A different methodology is used to estimate CH₄ generation at MSW landfills between 2010 to 2022. Recent inventories prior to the 1990-2020 *Inventory* did not separately present CH₄ generation, CH₄ recovery, or CH₄ oxidation from MSW landfills after 2005 because the methodology switched to using the directly reported net CH₄ emissions plus a scale-up factor (discussed in Step 4) between 2005 to the current *Inventory* year. In response to various queries and comments, estimates for CH₄ generation, CH₄ recovery, and CH₄ oxidation have been added to the 1990 to 2020 *Inventory* and will be updated annually. The methodology developed to estimate CH₄ generation between 2010 to 2022 is described below.

Step 3: Estimate CH₄ Emissions Avoided from MSW Landfills

Between 1990 to 2009, the estimated landfill gas recovered per year (R) at MSW landfills is based on a combination of four databases that include recovery from flares and/or landfill gas-to-energy projects:

- a database developed by the Energy Information Administration (EIA) for the voluntary reporting of greenhouse gases (EIA 2007),
- a database of LFGE projects that is primarily based on information compiled by EPA LMOP (EPA 2016),
- the flare vendor database (contains updated sales data collected from vendors of flaring equipment), and the
- EPA's GHGRP MSW landfills database (EPA 2015a).¹⁷⁷

Between 2010 and 2022, the estimated R at MSW landfills is calculated using directly reported annual quantities of R from EPA's GHGRP (EPA 2022) plus a scale-up factor to account for recovery from MSW landfills that may not be reporting to the GHGRP. The development of the scale-up factor is detailed under Step 4a. A scale-up factor of 9 percent and 11 percent is applied to the total R from EPA's GHGRP from 2010 to 2016 and 2017 to 2022, respectively. In 2022, the *Inventory* team compared the total R from EPA's GHGRP and EPA's LMOP 2021 database (EPA 2021); total R between the two databases were within a reasonable range, but higher in the LMOP 2021 database. The GHGRP data consist of mandatory, annually updated facility-specific data, while the LMOP database includes the GHGRP data in addition to voluntary, intermittent facility-specific data for facilities that do not report to the GHGRP.

Step 3a: Estimate CH₄ Emissions Avoided Through Landfill Gas-to-Energy (LFGE) and Flaring Projects for 1990 to 2009

The quantity of CH₄ avoided due to LFGE systems was estimated based on information from three sources: (1) a database developed by the EIA for the voluntary reporting of greenhouse gases (EIA 2007); (2) a database compiled by LMOP and referred to as the LFGE database for the purposes of this inventory (EPA 2016); and (3) the GHGRP MSW landfills dataset (EPA 2015a).

The EIA database includes location information for landfills with LFGE projects, estimates of CH₄ reductions, descriptions of the projects, and information on the methodology used to determine the CH₄ reductions. In general, the CH₄ reductions for each reporting year were based on the measured amount of landfill gas collected and the percent CH₄ in the gas.

For the LFGE database, data on landfill gas flow and energy generation (i.e., MW capacity) were used to estimate the total direct CH₄ emissions avoided due to the LFGE project.

The GHGRP MSW landfills database contains the most detailed data on landfills that reported under EPA's GHGRP for years 2010 through 2015, however the amount of CH₄ recovered is not specifically allocated to a flare versus a LFGE project. The allocation into flares or LFGE was performed by matching landfills to the EIA and LMOP databases for LFGE projects and to the flare database for flares. Detailed information on the landfill name, owner or operator, city, and state are available for both the EIA and LFGE databases; consequently, it was straightforward to identify landfills that were in

¹⁷⁷ The 2015 GHGRP dataset is used in the GHGRP MSW landfills dataset described in Step 3a. The flare database is no longer updated because the methodology changed such that the directly reported net methane emissions are used. The GHGRP dataset is available through Envirofacts <http://www.epa.gov/enviro/facts/ghg/search.html>.

both databases against those in EPA's GHGRP MSW landfills database. The EPA's GHGRP MSW landfills database was first introduced as a source for recovery data for the 1990 to 2013 *Inventory*. The GHGRP MSW landfills database contains facility-reported data that undergoes rigorous verification and is considered to contain the least uncertain data of the four databases. However, this database only contains a portion of the landfills in the United States (although, presumably the highest emitters since only those landfills that meet the methane generation threshold must report) and only contains data from 2010 and later. For landfills in this database, methane recovery data reported data for 2010 and later were linearly backcasted to 1990, or the date the landfill gas collection system at a facility began operation, whichever is earliest.

A destruction efficiency of 99 percent was applied to amounts of CH₄ recovered to estimate CH₄ emissions avoided for all recovery databases. This value for destruction efficiency was selected based on the range of efficiencies (86 to 99+ percent) recommended for flares in EPA's *AP-42 Compilation of Air Pollutant Emission Factors*, Draft Chapter 2.4, Table 2.4-3 (EPA 2008). A typical value of 97.7 percent was presented for the non-methane components (i.e., volatile organic compounds and non-methane organic compounds) in test results (EPA 2008). An arithmetic average of 98.3 percent and a median value of 99 percent are derived from the test results presented in EPA 2008. Thus, a value of 99 percent for the destruction efficiency of flares has been used in *Inventory* methodology. Other data sources supporting a 99 percent destruction efficiency include those used to establish New Source Performance Standards (NSPS) for landfills.

The same landfill may be included one or more times across these four databases before RTI data cleaning. To avoid double- or triple- counting CH₄ recovery, the landfills across each database were compared and duplicates identified. A hierarchy of recovery data is used based on the certainty of the data in each database. In summary, the GHGRP > EIA > LFGE > flare vendor database.

If a landfill in the GHGRP MSW landfills database was also in the EIA, LFGE, and/or flare vendor database, the avoided emissions were only based on EPA's GHGRP MSW landfills database to avoid counting the recovery amounts multiple times across the different databases. In other words, the CH₄ recovery from the same landfill was not included in the total recovery from the EIA, LFGE, or flare vendor databases. While the GHGRP contains facility-reported information on MSW Landfills starting in the year 2010, EPA has backcasted GHGRP emissions to the year 2005 in order to merge the two methodologies (more information provided in Steps 4a and 4b). Prior to 2005, if a landfill in EPA's GHGRP was also in the LFGE or EIA databases, the landfill gas project information, specifically the project start year, from either the LFGE or EIA databases was used as the cutoff year for the estimated CH₄ recovery in the GHGRP database. For example, if a landfill reporting under EPA's GHGRP was also included in the LFGE database under a project that started in 2002 that is still operational, the CH₄ recovery data in the GHGRP database for that facility was backcasted to the year 2002 only.

If a landfill in the EIA database was also in the LFGE and/or the flare vendor database, the CH₄ recovery was based on the EIA data because landfill owners or operators directly reported the amount of CH₄ recovered using gas flow concentration and measurements, and because the reporting accounted for changes over time. The EIA database only includes facility-reported data through 2006; the amount of CH₄ recovered in this database for years 2007 and later were assumed to be the same as in 2006. Nearly all (93 percent) of landfills in the EIA database also report to EPA's GHGRP.

If both the flare data and LFGE recovery data were available for any of the remaining landfills (i.e., not in the EIA or EPA's GHGRP databases), then the CH₄ recovered were based on the LFGE data, which provides reported landfill-specific data on gas flow for direct use projects and project capacity (i.e., megawatts) for electricity projects. The LFGE database is based on the most recent EPA LMOP database (published annually). The remaining portion of avoided emissions is calculated by the flare vendor database, which estimates CH₄ combusted by flares using the midpoint of a flare's reported capacity. Given that each LFGE project is likely to also have a flare, double counting reductions from flares and LFGE projects in the LFGE database was avoided by subtracting emission reductions associated with LFGE projects for which a flare had not been identified from the emission reductions associated with flares (referred to as the flare correction factor).

Step 3b: Estimate CH₄ Emissions Avoided Through Flaring for the Flare Database for 1990 to 2009

To avoid double counting, flares associated with landfills in EPA's GHGRP, EIA and LFGE databases were not included in the total quantity of CH₄ recovery from the flare vendor database. As with the LFGE projects, reductions from flaring landfill gas in the EIA database were based on measuring the volume of gas collected and the percent of CH₄ in the gas. The information provided by the flare vendors included information on the number of flares, flare design flow rates or flare dimensions, year of installation, and generally the city and state location of the landfill. When a range of design flare flow rates was provided by the flare vendor, the median landfill gas flow rate was used to estimate CH₄ recovered from each remaining flare (i.e., for each flare not associated with a landfill in the EIA, EPA's GHGRP, or LFGE databases).

Several vendors have provided information on the size of the flare rather than the flare design gas flow rate for most years of the *Inventory*. Flares sales data has not been obtained since the 1990 to 2015 *Inventory* year, when the net CH₄ emission directly reported to EPA's GHGRP began to be used to estimate emission from MSW landfills.

To estimate a median flare gas flow rate for flares associated with these vendors, the size of the flare was matched with the size and corresponding flow rates provided by other vendors. Some flare vendors reported the maximum capacity of the flare. An analysis of flare capacity versus measured CH₄ flow rates from the EIA database showed that the flares operated at 51 percent of capacity when averaged over the time series and at 72 percent of capacity for the highest flow rate for a given year. For those cases when the flare vendor supplied maximum capacity, the actual flow was estimated as 50 percent of capacity. Total CH₄ avoided through flaring from the flare vendor database was estimated by summing the estimates of CH₄ recovered by each flare for each year.

Step 3c: Correct Overestimation of CH₄ Emissions Avoided Through Flaring for 1990 to 2009

If comprehensive data on flares were available, each LFGE project in EPA's GHGRP, EIA, and LFGE databases would have an identified flare because it is assumed that most LFGE projects have flares. However, given that the flare vendor database only covers approximately 50 to 75 percent of the flare population, an associated flare was not identified for all LFGE projects. These LFGE projects likely have flares, yet flares were unable to be identified for one of two reasons: 1) inadequate identifier information in the flare vendor data, or 2) a lack of the flare in the flare vendor database. For those projects for which a flare was not identified due to inadequate information, CH₄ avoided would be overestimated, as both the CH₄ avoided from flaring and the LFGE project would be counted. To avoid overestimating emissions avoided from flaring, the CH₄ avoided from LFGE projects with no identified flares was determined and the flaring estimate from the flare vendor database was reduced by this quantity (referred to as a flare correction factor) on a state-by-state basis. This step likely underestimates CH₄ avoided due to flaring but was applied to be conservative in the estimates of CH₄ emissions avoided.

Additional effort was undertaken to improve the methodology behind the flare correction factor for the 1990 to 2009 and 1990 to 2014 inventory years to reduce the total number of flares in the flare vendor database that were not matched to landfills and/or LFGE projects in the EIA and LFGE databases. Each flare in the flare vendor database not associated with a LFGE project in the EIA, LFGE, or EPA's GHGRP databases was investigated to determine if it could be matched. For some unmatched flares, the location information was missing or incorrectly transferred to the flare vendor database and was corrected during the review. In other instances, the landfill names were slightly different between what the flare vendor provided, and the actual landfill name as listed in the EIA, LFGE and EPA's GHGRP databases. The remaining flares did not have adequate information through the name, location, or owner to identify it to a landfill in any of the recovery databases or through an Internet search; it is these flares that are included in the flare correction factor for the current inventory year.

A large majority of the unmatched flares are associated with landfills in the LFGE database that are currently flaring but are also considering LFGE. These landfills projects considering a LFGE project are labeled as candidate, planned, or construction in the LFGE database. The flare vendor database was improved in the 1990 to 2009 inventory year to match flares with operational, shutdown as well as candidate, potential, and construction LFGE projects, thereby reducing the total number of unidentified flares in the flare vendor database, all of which are used in the flare correction factor. The results of this effort significantly decreased the number of flares used in the flare correction factor, and consequently, increased recovered flare emissions, and decreased net emissions from landfills for the 1990 through 2009 *Inventory*. The revised state-by-state flare correction factors were applied to the entire *Inventory* time series (RTI 2010).

Step 4: Estimate CH₄ Emissions from MSW Landfills for 1990 to 2009

Methane emissions from MSW Landfills between 1990 and 2004 are estimated by subtracting the total annual amount of CH₄ recovered from the estimated CH₄ generation (see Equation A-67).

Methane emissions from MSW Landfills between 2005 to 2009 are estimated via a different methodology as described in the remainder of this step. During preparation of the 1990 to 2015 *Inventory*, EPA engaged with stakeholders both within and outside of the landfill industry on the methodology used in the *Inventory*, the data submitted by facilities under EPA's GHGRP Subpart HH for MSW Landfills, and the application of this information as direct inputs to the MSW landfill methane emissions estimates in the 1990 to 2015 *Inventory*. Based on discussions with stakeholders, EPA developed several options for improving the *Inventory* through methodological changes and moved forward with using the directly reported net GHGRP methane emissions from 2010 to 2015 for MSW landfills in the 1990 to 2015 *Inventory*.

The *Inventory* methodology now uses directly reported net CH₄ emissions for the 2010 to 2022 reporting years from EPA's GHGRP to backcast emissions for 2005 to 2009. The emissions for 2005 to 2009 are recalculated each year the *Inventory* is published to account for the additional year of reported data and any revisions that facilities make to past GHGRP reports. When EPA verifies the greenhouse gas reports, comparisons are made with data submitted in earlier reporting years and errors may be identified in these earlier year reports. Facility representatives may submit revised reports for any reporting year in order to correct these errors. Facilities reporting to EPA's GHGRP that do not have landfill gas collection and control systems use the FOD method. Facilities with landfill gas collection and control must use both the FOD method and a back-calculation approach. The back-calculation approach starts with the amount of CH₄ recovered and works back through the system to account for gas not collected by the landfill gas collection and control system (i.e., the collection efficiency).

Including the GHGRP net emissions data was a significant methodological change from the FOD method previously described in Steps 1 to 3 and only covered a portion of the *Inventory* time series. Therefore, EPA needed to merge the previous method with the new (GHGRP) dataset to create a continuous time series and avoid any gaps or jumps in estimated emissions in the year the GHGRP net emissions are first included (i.e., 2010).

To accomplish this, EPA backcasted GHGRP net emissions to 2005 to 2009 and added a scale-up factor to account for emissions from landfills that do not report to the GHGRP. A description of how the scale-up factor was determined and why the GHGRP emissions were backcasted are included below as Step 4a and Step 4b, respectively. The methodology described in this section was determined based on the good practice guidance in Volume 1: Chapter 5 Time Series Consistency of the *2006 IPCC Guidelines*. Additional details including other options considered are included in RTI (2017a) and RTI (2018).

Step 4a: Developing and Applying the Scale-up Factor for MSW Landfills for 2005 to 2009

Landfills that do not meet the reporting threshold are not required to report to the GHGRP. As a result, the GHGRP dataset is only partially complete when considering the universe of MSW landfills. In theory, national emissions from MSW landfills equals the emissions from landfills that report to the GHGRP plus emissions from landfills that do not report to the GHGRP. Therefore, for completeness, a scale-up factor had to be developed to estimate the amount of emissions from the landfills that do not report to the GHGRP. A scale-up factor of 9 percent is applied annually to the net GHGRP CH₄ emissions between 2005 to 2016.

To develop the 9 percent scale-up factor, EPA completed four main steps:

1. EPA determined the number of landfills that do not report to the GHGRP (hereafter referred to as the non-reporting landfills). Source databases included the LMOP database 2017 (EPA 2017) and the WBJ Directory 2016 (WBJ 2016). This step identified 1,544 landfills that accepted MSW between 1940 and 2016 and had never reported to the GHGRP. These landfills and the data collected were compiled into the 2016 Non-Reporting Landfills Database.
2. EPA estimated annual waste disposed and the total waste-in-place (WIP) at each non-reporting landfill as of 2016. Both databases include critical details about individual landfills to estimate annual methane emissions, including the year waste was first accepted, the year the landfill closed (as applicable), and the estimated amount of waste disposed. But not all details are included for all landfills. A total of 969 of the 1,544 landfills (63 percent) contained the critical information necessary to estimate WIP.
 - a. For 234 non-reporting landfills, there was not enough information in the source databases to estimate WIP.
 - b. For 341 of the non-reporting landfills, WIP could be estimated with assumptions that either (i) "forced" the year that waste was first accepted as 30 years prior to the landfill closure year (if a closure date was included); or (ii) "forced" a closure year of 2016 if the landfill was known to be closed and a closure year was not included in the source database.
 - c. The database was reviewed by industry and staff from LMOP at this stage to help fill data gaps and rectify discrepancies between individual landfills across the source databases, which improved the WIP estimates by landfill and overall.
3. EPA summed the total WIP for the non-reporting landfills. Using the assumptions mentioned above, the total WIP in 2016 across the non-reporting landfills was approximately 0.922 billion MT.

4. EPA calculated the scale-up factor (9 percent) by dividing the non-reporting landfills WIP (0.92 billion MT) by the sum of the GHGRP WIP and the non-reporting landfills WIP (10.0 billion MT).

Table A-218: Revised Waste-in-Place (WIP) for GHGRP Reporting and Non-Reporting Landfills in 2016

Category	Estimated WIP (Billion metric tons)	Percentage
Non-reporting facilities	0.92	9 percent (the applied scale-up factor)
GHGRP facilities	9.1	91 percent
Total	10.0	100 percent

Note: The scale-up factor is applied in each year the GHGRP reported emissions are used in the *Inventory*.

Step 4b: Backcasting GHGRP Emissions for MSW Landfills for 2005 to 2009 to Ensure Time Series Consistency

Regarding the time series and as stated in *2006 IPCC Guidelines Volume 1: Chapter 5 Time Series Consistency* (IPCC 2006), “the time series is a central component of the greenhouse gas inventory because it provides information on historical emissions trends and tracks the effects of strategies to reduce emissions at the national level. All emissions in a time series should be estimated consistently, which means that as far as possible, the time series should be calculated using the same method and data sources in all years” (IPCC 2006). Chapter 5 however, does not recommend backcasting emissions to 1990 with a limited set of data and instead provides guidance on techniques to splice, or join methodologies together. One of those techniques is referred to as the overlap technique. The overlap technique is recommended when new data becomes available for multiple years, which was the case with the GHGRP data, where directly reported net CH₄ emissions data became available for more than 1,200 MSW landfills beginning in 2010. The GHGRP emissions data had to be merged with emissions from the FOD method to avoid a drastic change in emissions in 2010, when the datasets were combined. EPA also had to consider that according to IPCC’s good practice, efforts should be made to reduce uncertainty in *Inventory* calculations and that, when compared to the GHGRP data, the FOD method presents greater uncertainty.

In evaluating the best way to combine the two datasets, EPA considered either using (1) the FOD method from 1990 to 2009, or (2) using the FOD method for a portion of that time series and backcasting the GHGRP emissions data to a year where emissions from the two methodologies aligned. Plotting the backcasted GHGRP emissions against the emissions estimates from the FOD method showed an alignment of the data in 2004 and later years which facilitated the use of the overlap technique while also reducing uncertainty. Therefore, EPA decided to backcast the GHGRP emissions from 2009 to 2005 only, to merge the datasets and adhere to the IPCC good practice guidance.

EPA used the Excel Forecast function to backcast net methane emissions using the GHGRP data. The forecast function is used to predict a future value by using existing values, but EPA has applied it to predict previous values. Although it is not ideal, it allowed for expeditious implementation. In the forecast function, the known values are existing x-values and y-values (i.e., the years and data for the GHGRP, 2010 to 2015). The unknown y-values are the years to be estimated (i.e., all years prior to 2009). The following Excel formula was used: =FORECAST(year to backcast, GHGRP data for 2010 to 2015, years 2010 to 2015). The forecast function is a linear regression; thus, it will not account for annual fluctuations in CH₄ emissions when used for multiple years.

An important factor in this approach is that the backcasted emissions for 2005 to 2009 are subject to change with each *Inventory* because the GHGRP dataset may change as facilities revise their annual reports. The revisions are generally minor considering the entire GHGRP dataset and EPA has not determined any revisions to the backcasting approach or scale-up factor are necessary to date.

Step 5: Estimate CH₄ Emissions from MSW Landfills for 2010 to 2016

CH₄ emissions directly reported to EPA’s GHGRP are used for 2010 to 2016. Inherent in these direct emissions are the use of various GHGRP default emission factors such as the gas collection and control system collection efficiencies (where applicable), decay rate (k), and degradable organic carbon (DOC).

Facilities reporting to Subpart HH of the GHGRP can report their k and DOC values under one of three waste type options: (1) Bulk waste option, where all waste is accounted for within one bulk k and DOC value; (2) Modified bulk

waste option, where waste disposed of at the landfill can be binned into bulk MSW excluding inerts and construction and demolition waste, construction and demolition waste, and inerts; and (3) Waste Composition option, where waste disposed of can be delineated into specific waste streams (i.e., food waste, garden waste, textiles, etc.) OR where facilities report a known quantity of inert waste and consider the remaining waste as bulk MSW (using the same k and DOC value for MSW as the bulk waste option).

The GHGRP requires facilities with a gas collection and control system to report their emissions using both a forward-estimating (i.e., using a first order decay approach, accounting for soil oxidation) and a back-calculating (i.e., using methane recovery and collection efficiency data, accounting for soil oxidation) method as described in Chapter 7 of this *Inventory*. To determine collection efficiency, facilities are required to report the amount of waste-in-place (surface area and soil depth) at their landfill as categorized by one of five area types (see Table A-219).

Table A-219: Table HH-3 to Subpart HH of the EPA’s Greenhouse Gas Reporting Program, Area Types Applicable to the Calculation of Gas Collection Efficiency

Description	Landfill Gas Collection Efficiency
A1: Area with no waste-in-place	Not applicable, do not use this area in the calculation
A2: Area without active gas collection, regardless of cover type	CE2: 0%
A3: Area with daily soil cover and active gas collection	CE3: 60%
A4: Area with an intermediate soil cover, or a final soil cover not meeting the criteria for A5 below, and active gas collection	CE4: 75%
A5: Area with a final soil cover of 3 feet or thicker of clay or final cover (as approved by the relevant agency) and/or geomembrane cover system and active gas collection	CE5: 95%
Weighted average collection efficiency for landfills:	
Area weighted average collection efficiency for landfills	$CE_{ave1} = (A2 \times CE2 + A3 \times CE3 + A4 \times CE4 + A5 \times CE5) / (A2 + A3 + A4 + A5)$

If facilities are unable to bin their waste into these area types, they are instructed to use 0.75, or 75 percent as a default value. In the EPA’s original rulemaking for the GHGRP, the EPA proposed this default collection efficiency of 75 percent because it was determined to be a reasonable central-tendency default considering the availability of data such as surface monitoring under the EPA’s New Source Performance Standards for MSW Landfills (40 CFR Part 60 Subpart WWW), which suggested that gas collection efficiencies generally range from 60 to 95 percent. This 75 percent default gas collection efficiency value only applies to areas at the landfill that are under gas collection and control; for areas of the landfill that are not under gas collection and control, a gas collection efficiency of 0 percent is applied.

The 9 percent scale-up factor is applied to the net annual emissions reported to the GHGRP for 2010 to 2016 as is done for 2005 to 2009 because the GHGRP does not capture emissions from all landfills in the United States.

Step 6: Estimate CH₄ Emissions from MSW Landfills for 2017 to 2022

The same methodology described in Step 5 is used to estimate CH₄ emissions from MSW Landfills for 2017 to 2022, except the scale-up factor applied is different (11 percent instead of 9 percent). The scale-up factor was initially developed to use the GHGRP reported data and account for the remaining subset of landfills that are not required to report to the GHGRP. The EPA acknowledges there are uncertainties associated with the 9 percent scale-up factor and underlying landfill-specific data used to develop the Non-Reporting Landfills database. Specifically, the GHGRP allows facilities to off-ramp (i.e., stop reporting to the GHGRP) after meeting certain criteria; therefore, the number of facilities and WIP reported under the GHGRP will vary year to year. Nearly 200 facilities have off-ramped from the GHGRP to date, which means there is now more WIP for non-reporting landfills than there was in the 2016 scale-up factor analysis. Reassessment of the scale-up factor at regular intervals to account for changes in the GHGRP dataset and LMOP database is considered good practice and was therefore included in the Planned Improvements section for a previous (1990 to 2018) *Inventory*.

The methodology used to revise the scale-up factor largely followed that to develop the 2016 Non-Reporting Landfills Database, as summarized below, except that the scale-up factor is now a time-based threshold considering total waste disposed in the 50 years prior to 2020 (i.e., between 1970 to 2020) instead of total waste-in-place for all non-reporting

landfills. This methodological change was made in response to reviewer comments on the 1990 to 2019 *Inventory*. Both a 30-year and a 50-year time-based threshold were evaluated for the scale-up factor under the knowledge that peak production of landfill gas typically occurs within 5 to 7 years after wastes are first disposed, almost all gas is produced within 20-30 years after waste is disposed, and small quantities of gas may continue to be emitted from a landfill for 50 or more years (ASTDR, 2001). EPA decided to use the 50-year threshold for the scale-up factor applied between 2017 to 2020 for three reasons: (1) because 50 years aligns with the IPCC recommendation of using 50 years of historical waste disposal data in the FOD model to estimate CH₄ generation; (2) expert knowledge that MSW landfills can generate CH₄ for up to 50 years (ASTDR, 2001); and (3) because the Non-Reporting Landfills Database cannot estimate waste disposal for several hundred landfills where not enough data are available. The 50-year threshold for the scale-up factor is a conservative approach considering the number of assumptions and missing data in the Non-Reporting Landfills Database.

Details on the revised 2020 scale-up factor are included in RTI (2021) and the general methodology is summarized in the remainder of this Step.

1. EPA streamlined the layout of the 2016 Non-Reporting Landfills Database to remove extraneous columns, clearly present the landfill-specific data from the main sources (i.e., the 2017 LMOP Database [EPA 2017] and the WBJ Directory 2016 [WBJ 2016]), and the calculation columns that yield the start year, closure year, and WIP data used to estimate the total WIP at all non-reporting landfills. The database is hereafter referred to as the 2018 Non-Reporting Landfills Database.
2. EPA added in new or updated data for existing non-reporting landfills and added in entries for new non-reporting landfills.
 - a. Added the 194 landfills that have off-ramped from the GHGRP as of 2020 (EPA 2022) into the Non-Reporting Landfills Database.
 - b. Cross-referenced and updated the 2017 LMOP Database (EPA 2017) information with the 2021 LMOP Database (EPA 2021) information. Approximately 217 new cases or updated information from the 2021 LMOP Database were added or revised.
 - c. These revisions increased the count of non-reporting landfills from 1,544 landfills to 1,672 landfills, a net increase of 128 landfills from the 2016 Non-Reporting Landfills Database; however, only 1,069 landfills had enough information for the scale-up factor calculations.
3. EPA conducted additional quality control checks on calculations in the 2016 Non-Reporting Landfills Database and rectified identified errors, which resulted in an increase of 38,498,070 MT of waste from the 2016 Non-Reporting Landfills Database.
 - a. A formula error was identified that under-estimated the WIP for landfills with a permitted end year after 2016, especially for those landfills that had reported closure dates in 2030 or later. For example, if the start year was 1980 and the permitted closure year was 2040, the formula was estimating 50 years when, for the purposes of this exercise, the number of years should have been 36 years. Dividing the WIP by 60 years results in a lower annual waste disposal value than dividing the WIP by 36 years (2016-1980). The methodology calculates an annual disposal rate for each landfill and then applies the annual disposal rate to 2016 minus the start year.
 - b. The WIP data year was not pulled from the 2017 LMOP Database and it was assumed the WIP data were from 2016 unless otherwise noted. The WIP year is now included in the 2018 Non-Reporting Landfills Database. The WBJ Directory does not present the year the WIP data are from, thus we assumed each data point was from 2016. These assumptions underestimate the amount of WIP for a large majority of the landfills where the WIP data year is not reported.
4. EPA estimated annual waste disposed at each non-reporting landfill as of 2020. Where available, the databases include details about individual landfills, including the year waste was first accepted, the year the landfill closed (as applicable), and the estimated amount of waste disposed. When enough data were available, EPA estimated total WIP by calculating an annual waste disposal rate and multiplied that by the number of operating years up to the closure year, or 2018 (if the landfill was known or assumed to be open). EPA used a tiered methodology when a landfill with critical information was included in more than one database:

Tier 1: If the landfill has off-ramped from the GHGRP, use the Subpart HH WIP value (and update to include assumed waste disposed between the year the landfill off-ramped to 2020, if operational during that time frame).

Tier 2: If the landfill is in the 2021 LMOP Database, use the 2021 LMOP WIP value.

Tier 3: Otherwise, EPA used the average of the estimated WIP value that was forced or provided from the 2016 Non-reporting Landfill Database industry and LMOP reviewers.

5. Annual waste disposal was then calculated by dividing the total WIP by the number of operational years for each landfill between 1970 to 2020 (i.e., 50 years).
 - a. A total of 1,352 of the 1,672 landfills (approximately 81 percent) contained enough critical information necessary to estimate the 2020 WIP (i.e., first year of operation, either total WIP or annual waste disposal data, and either an indication the landfill was still operating or the closure date). It is important to note that the WIP and annual waste disposal data are estimates. The quality of the source data for WIP and annual waste disposed have not been individually verified by the EPA team. In the case of the GHGRP data, the annual waste disposal quantities are either estimates using defined methodologies or actual waste disposed from tipping receipts. In general, most landfills have relied on tipping receipts for the past decade, meaning that annual waste disposed several decades ago are estimates.
 - b. For 593 of the 1,672 landfills (35 percent), WIP could be estimated with assumptions that either (i) “forced” the year that waste was first accepted as 30 years prior to the landfill closure year (if a closure year was included); or (ii) forced a closure year of 2018 if the landfill was known or thought to be open and a closure year was not included in the source database. These are the same general assumptions applied in the 2016 Non-Reporting Landfills Database.
6. For 321 of the 1,672 landfills (19 percent), there was not enough information in the source databases to estimate WIP, thus no WIP data was calculated for these facilities, which underestimates the total WIP and total waste disposed between 1970 to 2020 for the non-reporting landfills. EPA summed the total waste disposed for the 50-year threshold (1970 to 2020) for the non-reporting landfills, yielding 1.33 billion MT.
7. EPA calculated the scale-up factor (11 percent) by dividing the waste disposed by non-reporting landfills (1.33 billion MT) by the sum of the reporting landfills’ waste disposed and the total of both categories (12.3 billion MT).

Table A-220: Total Waste Disposed over 50 Years (1970-2020) for GHGRP Reporting and Non-reporting Landfills in 2020

Category	Estimated Waste Disposed (billion metric tons)	Percentage
Non-reporting facilities	1.33	11 percent (the applied scale-up factor)
GHGRP facilities	11.0	89 percent
Total	12.33	100 percent

An 11 percent scale-up factor is applied annually for 2017 to 2022 because the GHGRP does not capture emissions from all landfills in the United States. In future inventories, the scale-up factor will be reassessed to include additional facilities that off-ramp from the GHGRP, revisions to the LMOP Database, and adjust the start and end years for a 50-year threshold.

Step 7: Estimate CH₄ Generation at Industrial Waste Landfills for 1990 to the Current Inventory Year

A Tier 2 approach (IPCC 2006) is used to estimate annual emissions from industrial waste landfills. A tailored IPCC waste model, based on the FOD method and country-specific defaults, is exclusively used for 1990 to 2022. For the FOD method, methane generation is based on nationwide industrial production data from two major sectors—pulp and paper, and food and beverage manufacturing—to which a national average disposal factor is applied, separately for each sector.

The methodology is not Tier 3 (i.e., it is not landfill-specific) because data for individual landfills are limited. Table A-215 presents the amount of industrial production data and estimated amount of industrial waste landfilled for select years.

The FOD method is presented in Equation A-67 and is similar to Equation HH-6 in CFR Part 98.343 for MSW landfills, and Equation TT-6 in CFR Part 98.463 for industrial waste landfills.

Industrial waste landfills receive waste from factories, processing plants, and other manufacturing activities. In national inventories prior to the 1990 through 2005 inventory, CH₄ generation at industrial landfills was estimated as seven percent of the total CH₄ generation from MSW landfills, based on a study conducted by EPA (1993). In 2005, the methodology was updated and improved by using activity factors (industrial production levels) to estimate the amount of industrial waste landfilled each year, and by applying the FOD model to estimate CH₄ generation. A nationwide survey of industrial waste landfills found that most of the organic waste placed in industrial waste landfills originated from two sectors: food processing (meat, vegetables, fruits) and pulp and paper (EPA 1993). Data for annual nationwide production for the food and beverage processing and pulp and paper sectors were taken from industry and government sources for recent years and estimates were developed for production for the earlier years for which data were not available.

For the pulp and paper sector, production data published by the Lockwood-Post's Directory were used for years 1990 to 2001 and production data published by the Food and Agriculture Organization were used for years 2002 to 2022. An extrapolation based on U.S. real gross domestic product was used for years 1940 through 1964.

For the food and beverage processing sector, production data were obtained from the U.S. Department of Agriculture for the years 1990 to 2022 (ERG 2023). An extrapolation based on U.S. population was used for the years 1940 through 1989.

In addition to production data for the pulp and paper and food processing sectors, the following inputs are needed to use the FOD model for estimating CH₄ generation from industrial waste landfills: 1) quantity of waste that is disposed in industrial waste landfills (as a function of production), 2) CH₄ generation potential (L₀) from which a DOC value can be calculated, and 3) the decay rate constant (k).

Research into waste generation and disposal in landfills for the pulp and paper sector indicated that the quantity of waste landfilled was about 0.050 MT/MT (5 percent) of product. This waste disposal factor is applied to all years of the time series for the pulp and paper sector. A waste disposal factor of 0.0486 MT/MT (4.86 percent) of product (RTI 2006 using data from EPA 1993) is applied for the food processing sector between 1990 to 2009. A revised waste disposal factor of 6 percent (based on recent survey data from the food and beverage sector, see FWRA 2016) is applied to the food and beverage production data between 2010 to the current year. These waste disposal factors are applied to estimates of annual production to estimate annual waste disposal in industrial waste landfills (see Table A-215 for select years). Estimates for DOC were derived from available data (EPA, 2015b; Heath et al., 2010; NCASI, 2005; Kraft and Orender, 1993; NCASI 2008; Flores et al. 1999 as documented in RTI 2015a). The DOC value for industrial pulp and paper waste is estimated at 0.15 (L₀ of 49 m³/MT); the DOC value for industrial food waste is estimated as 0.26 (L₀ of 128 m³/MT) (RTI 2015; RTI 2014). Estimates for k were taken from the default values in the *2006 IPCC Guidelines*; the value of k given for food waste with disposal in a wet temperate climate is 0.19 yr⁻¹, and the value given for paper waste is 0.06 yr⁻¹.

A literature review was conducted for the 1990 to 2010 and 1990 to 2014 inventory years with the intent of updating values for L₀ (specifically DOC) and k in the pulp and paper sector (RTI 2014). Where pulp and paper mill wastewater treatment residuals or sludge are the primary constituents of pulp and paper waste landfilled, values for k available in the literature range from 0.01/yr to 0.1/yr, while values for L₀ range from 50 m³/Mt to 200 m³/Mt.¹⁷⁸ Values for these factors are highly variable and are dependent on the soil moisture content, which is generally related to rainfall amounts. At this time, sufficient data were available through EPA's GHGRP to warrant a change to the L₀ (DOC) from 99 to 49 m³/MT, but sufficient data were not obtained to warrant a change to k. EPA will consider an update to the k values for the pulp and paper sector as new data arises and will work with stakeholders to gather data and other feedback on potential changes to these values.

As with MSW landfills, a similar trend in disposal practices from unmanaged landfills, or open dumps to managed landfills was expected for industrial waste landfills; therefore, the same timeline that was developed for MSW landfills

¹⁷⁸ Sources reviewed included Heath et al. 2010; Miner 2008; Skog 2008; Upton et al. 2008; Barlaz 2006; Sonne 2006; NCASI 2005; Barlaz 1998; and Skog and Nicholson 2000.

was applied to the industrial landfills to estimate the average MCF. That is, between 1940 and 1980, the fraction of waste that was land disposed transitioned from 6 percent managed landfills in 1940 and 94 percent open dumps to 100 percent managed landfills in 1980 and on. For wastes disposed of in unmanaged sites, an MCF of 0.6 was used and for wastes disposed of in managed landfills, an MCF of 1 was used, based on the recommended IPCC default values (IPCC 2006).

The parameters discussed above were used in the integrated form of the FOD model to estimate CH₄ generation from industrial waste landfills.

Step 8: Estimate CH₄ Oxidation from MSW and Industrial Waste Landfills

Step 8a: Estimate CH₄ Oxidation from Industrial Waste Landfills for 1990 to Present

A portion of the CH₄ escaping from a landfill oxidizes to CO₂ in the top layer of the soil. The amount of oxidation depends upon the characteristics of the soil and the environment. For purposes of this analysis, it was assumed that of the CH₄ generated, minus the amount of gas recovered for flaring or LFGE projects, 10 percent was oxidized in the soil (Jensen and Pipatti 2002; Mancinelli and McKay 1985; Czepiel et al 1996). The literature was reviewed in 2011 (RTI 2011) and 2017 (RTI 2017b) to provide recommendations for the most appropriate oxidation rate assumptions. It was found that oxidation values are highly variable and range from zero to over 100 percent (i.e., the landfill is considered to be an atmospheric sink by virtue of the landfill gas extraction system pulling atmospheric methane down through the cover). There is considerable uncertainty and variability surrounding estimates of the rate of oxidation because oxidation is difficult to measure and varies considerably with the presence of a gas collection system, thickness and type of the cover material, size and area of the landfill, climate, and the presence of cracks and/or fissures in the cover material through which methane can escape. IPCC (2006) notes that test results from field and laboratory studies may lead to over-estimations of oxidation in landfill cover soils because they largely determine oxidation using uniform and homogeneous soil layers. In addition, several studies note that gas escapes more readily through the side slopes of a landfill as compared to moving through the cover thus complicating the correlation between oxidation and cover type or gas recovery.

An oxidation factor of 0.10 (IPCC 2006) is applied for industrial waste landfills for the entire time series.

Step 8b: Estimate CH₄ Oxidation from MSW Landfills for 1990 to 2004

An oxidation factor of 0.10 (IPCC 2006) is applied for MSW Landfills between 1990 to 2004. A variety of oxidation factors (0.0, 0.10, 0.25, or 0.35) are applied for MSW landfills between 2005 to 2009 as described below. The oxidation factors applied for MSW landfills are based on IPCC 2006 (0.10) and scientific literature reviewed for the development of the GHGRP regulations (40 CFR Part 98). An annual weighted average of facility-reported oxidation factors from the GHGRP dataset are applied between 2005 to 2021. Between 2005 to 2009, the annual weighted average oxidation factor ranges from 11 percent to 15 percent. Between 2010 to 2016, the annual weighted average oxidation factor ranges from 17 to 21 percent; and from 2017 to 2022, the annual weighted average oxidation factor ranges from 21 to 23 percent (EPA 2022).

The annual amount of CH₄ oxidized is calculated for 1990 to 2004 by applying the 10 percent oxidation factor to the sum of CH₄ generation minus recovery as presented in Equation A-67. The annual amount of CH₄ oxidized is calculated for 2005 to present by solving for oxidation in Equation A-67 when CH₄ generation, R, and the net CH₄ emission values are known. In other words, when solving Equation A-70 below:

Equation A-70: Back-calculated Methane Oxidation

$$Ox = -(G_{CH_4,MSW} + R - CH_{4,Solid\ Waste})$$

where,

Ox	=	CH ₄ oxidized from MSW landfills before release to the atmosphere
CH _{4,Solid Waste}	=	Net CH ₄ emissions from MSW landfills
G _{CH₄,MSW}	=	CH ₄ generation from MSW landfills
R	=	CH ₄ recovered and combusted from MSW landfills.

The remainder of this step provides supporting documentation on the oxidation factors applied for MSW Landfills.

MSW landfills with landfill gas collection systems are generally designed and managed better to improve gas recovery. More recent research (2006 to 2012) than IPCC (2006) on landfill cover methane oxidation has relied on stable isotope techniques that may provide a more reliable measure of oxidation. Results from this recent research consistently point to higher cover soil methane oxidation rates than the IPCC (2006) default of 10 percent. A continued effort will be made to review the peer-reviewed literature to better understand how climate, cover type, and gas recovery influence the rate of oxidation at active and closed landfills. At this time, the IPCC recommended oxidation factor of 10 percent will continue to be used for all landfills for the years 1990 to 2004 and for industrial waste landfills for the full time series.

Step 8c: Estimate CH₄ Oxidation from MSW Landfills for 2005 to 2022

For years 2005 to 2022, net CH₄ emissions from MSW landfills as directly reported to EPA’s GHGRP, which include the adjustment for oxidation, are used. Subpart HH of the GHGRP includes default values for oxidation which are dependent on the mass flow rate of CH₄ per unit at the bottom of the surface soil prior to any oxidation, also known as methane flux rate. The oxidation factors included in the GHGRP (0, 0.10, 0.25, 0.35) are based on published, peer-reviewed literature and facility data provided through external stakeholder engagement. The EPA concluded, during review of both the literature and facility-reported emissions data, that simply revising the IPCC’s Tier 1 oxidation default of 10 percent to a new singular default oxidation value would not take into account the key variable - methane flux rate - entering the surface soil layer. More information regarding analysis of methane oxidation fractions can be found in the memorandums entitled “Review of Oxidation Studies and Associated Cover Depth in the Peer Reviewed Literature”, June 17, 2015 (RTI 2015b). More information about the landfill specific conditions required to use higher oxidation factors can be found in Table HH-4 of 40 CFR Part 98, Subpart HH, as shown below.

Table A-221: Table HH-4 to Subpart HH of Part 98—Landfill Methane Oxidation Fractions

Under these conditions:	Use this landfill methane oxidation fraction:
I. For all reporting years prior to the 2013 reporting year	
C1: For all landfills regardless of cover type or methane flux	0.10
II. For the 2013 reporting year and all subsequent years	
C2: For landfills that have a geomembrane (synthetic) cover or other non-soil barrier meeting the definition of final cover with less than 12 inches of cover soil for greater than 50% of the landfill area containing waste	0.10
C3: For landfills that do not meet the conditions in C2 above and for which you elect not to determine methane flux	0.10
C4: For landfills that do not meet the conditions in C2 or C3 above and that do not have final cover, or intermediate or interim cover ^a for greater than 50% of the landfill area containing waste	0.10
C5: For landfills that do not meet the conditions in C2 or C3 above and that have final cover, or intermediate or interim cover ^a for greater than 50% of the landfill area containing waste and for which the methane flux rate ^b is less than 10 grams per square meter per day (g/m ² /d)	0.35
C6: For landfills that do not meet the conditions in C2 or C3 above and that have final cover or intermediate or interim cover ^a for greater than 50% of the landfill area containing waste and for which the methane flux rate ^b is 10 to 70 g/m ² /d	0.25
C7: For landfills that do not meet the conditions in C2 or C3 above and that have final cover or intermediate or interim cover ^a for greater than 50% of the landfill area containing waste and for which the methane flux rate ^b is greater than 70 g/m ² /d	0.10

^a Where a landfill is in a state that does not have an intermediate or interim cover requirement, the landfill must have soil cover of 12 inches or greater in order to use an oxidation fraction of 0.25 or 0.35.

^b Methane flux rate (in grams per square meter per day; g/m²/d) is the mass flow rate of methane per unit area at the bottom of the surface soil prior to any oxidation and is calculated as follows:

For Equation HH-5 of this subpart, or for Equation TT-6 of subpart TT of this part,

$$MF = K \times G_{CH_4} / S_{Area}$$

For Equation HH-6 of this subpart,

$$MF = K \times \left(G_{CH_4} - \sum_{n=1}^N R_n \right) / S_{Area}$$

For Equations HH-7 of this subpart,

$$MF = K \times \left(\frac{1}{CE} \sum_{n=1}^N \left[\frac{R_n}{f_{Rec,n}} \right] \right) / S_{Area}$$

For Equation HH-8 of this subpart,

$$MF = K \times \left(\frac{1}{CE} \left\{ \sum_{n=1}^N \left[\frac{R_n}{f_{Rec,n}} \right] \right\} - \sum_{n=1}^N R_n \right) / S_{Area}$$

The EPA's GHGRP also requires landfills to report the type of cover material used at their landfill as: organic cover, clay cover, sand cover, and/or other soil mixtures.

The average oxidation factor applied between 2005 and 2022 ranges from 15 percent to 23 percent.

Table A-222: Applied Oxidation Factors for MSW Landfills

	1990	2005	2018	2019	2020	2021	2022
Applied oxidation factor	0.10	0.15	0.21	0.21	0.22	0.22	0.23

Source: weighted average of reported oxidation factors in net emissions from reporting facilities to GHGRP Subpart HH, EPA 2023.

Step 9: Estimate Total Net CH₄ Emissions for the *Inventory*

For 1990 to 2004, total net CH₄ emissions were calculated by adding emissions from MSW and industrial landfills, and subtracting CH₄ recovered and oxidized, as shown in Table 7-4. A different methodology is applied for 2005 to 2022 where directly reported net CH₄ emissions to EPA's GHGRP plus a scale-up factor to account for landfills that do not report to the GHGRP was applied. For 2005 to 2009, the directly reported GHGRP net emissions from 2010 to 2018 were used to backcast emissions for 2005 to 2009. Note that the emissions values for 2005 to 2009 are recalculated for each *Inventory* and are subject to change if facilities reporting to the GHGRP revise their annual greenhouse gas reports for any year. A 9 percent scale-up factor was applied annually to the net CH₄ reported to the GHGRP for 2005 to 2016, and an 11 percent scale-up factor was applied to the net CH₄ reported to the GHGRP for 2017 to 2022.

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